DISCRETE CHOICE, RECREATION DEMAND, AND CONSUMER SURPLUS

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Three topics are examined using discrete choice models to estimate demand and consumer surplus for recreation trips. The first topic involves recreation nonparticipation and the choice to participate in a recreational activity. In recreation demand models that examine the general population, nonparticipation is usually estimated as the probability mass on zero demand given a positive level of expected demand and a discrete distribution of demand outcomes. Researchers have attempted to improve predictions of nonparticipation by modifying the parameters of the demand distribution. This study departs from previous approaches by explicitly incorporating nonparticipation into the behavioral model. The choice to participate is described by a distribution of preferences combined with a choke price on individual demands to distinguish participants from nonparticipants. The model is applied to a recreational activity in South Carolina called shrimp baiting and is found to accurately predict nonparticipation and the size of the user group.

The second topic involves the estimating recreation demand models that account for fixed annual recreation fees. Models of recreation behavior have typically ignored the role of fixed annual fees, such as the fee for a recreational license, in determining choice and welfare. The second study demonstrates how techniques from the literature on discrete-continuous choice and two-part tariffs can address a situation where fixed annual fees are essential to determining the choice of a recreation site. Accounting for value captured by fixed fees can influence the way resource changes are assessed.

The third study proposes a new way to incorporate income effects in logit models with repeated choices. The repeated-logit specification, commonly viewed as a series of independent discrete choices, is instead viewed as a system of continuous demand equations. In the demand-system context, repeated logit satisfies integrability conditions for the existence of an underlying utility function while retaining desirable modeling properties such as allowing for income effects together with Marshallian cross-price effects. Relative to previous welfare measures for repeated logit, the proposed approach overcomes the problem of independent choice occasions and permits the computation of theoretically supported Hicksian welfare measures.

BIOGRAPHICAL SKETCH

Eric English grew up in Wayland, Massachusetts, and has since lived in Williamstown, Massachusetts; London; Vienna; New York City; Washington, D.C.; Ithaca, New York; Paris; and Boulder, Colorado. He has worked as a translator in German; a newspaper reporter; and an economist, first in the field of business litigation and currently in the field of resource valuation. He enjoys movies, food, and hiking.

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CHAPTER 1:

RECREATION NONPARTICIPATION AS CHOICE BEHAVIOR RATHER THAN STATISTICAL OUTCOME

In addition to demand and welfare estimation, models of recreation behavior should be able to provide reasonable predictions of the number of participants in a recreational activity. In models that attempt to address the issue, a common difficulty is the tendency to overestimate the size of the participant group and underestimate the extent of nonparticipation. Another difficulty is that welfare estimates often change substantially when models are adjusted to better predict nonparticipation. This article proposes a recreation demand model that estimates the number of participants quite accurately for the data examined while closely reproducing welfare estimates obtained from more commonly used methods.

Researchers may be interested in estimating changes in the number of recreation participants for several reasons. Public support for recreational amenities depends in part on the number and types of participants as well as the total demand for trips. Examining the participation rate may be especially important to understanding long-term changes in the popularity of certain activities. For activities that require a license, policies that affect the number of participants have direct consequences for license sales and revenue. If license fees are used to control the burden of use on a resource, policymakers may be interested in the welfare implications of alternative fee policies and the resulting changes in participation and demand.

This study examines a licensed recreational activity in South Carolina called shrimp baiting and finds that models available in the literature provide poor predictions of the number of recreation participants. Previous models have typically estimated nonparticipation as the mass on zero demand given positive expected demand and a discrete distribution of demand outcomes. In the proposed model nonparticipation arises from a distribution of preferences rather than a distribution of outcomes. Continuous preferences are mapped to discrete choice outcomes by estimating a choke price on individual demands that distinguishes participants from nonparticipants. Given the discrete nature of an individual's demand for trips and the likely hurdle effect of an annual license fee, the inclusion of a choke price for individual demands seems like a realistic refinement for the activity examined.

1.1 Literature Review

Interest in understanding the extent of nonparticipation first arose in the context of onsite recreation surveys in which nonusers were truncated from the data. Avoiding truncation bias requires an implicit estimate of the size of the nonuser group so that the demand response to price can be determined using valid cross-sections of the full population rather than conditional on positive trip demand. Smith and Desvousges (1985), Smith (1988) and Shaw (1988) were among the first to introduce estimators for truncated data, exploring a variety of continuous (such as Tobit) and discrete (such as Poisson) specifications. Grogger and Carson (1991) extended Shaw's truncated Poisson estimator to allow greater heterogeneity in observed demands using a negative binomial specification developed by Hausman, Hall, and Griliches (1984) and Cameron and Trivedi (1986). Around the same time full-population models evolved from zonal to individual-level specifications, requiring the development of Tobit or Poisson-type estimators that could account for censoring at zero and a large number of zero-demand observations (Bockstael et al. 1990; Smith 1988; Hellerstein 1992).

Truncated estimators predict the size of the nonuser group by fitting the observed pattern of positive demands to a truncated parametric distribution. Whether such an approach is adequate was questioned by Yen and Adamowicz (1994), who found large differences in welfare estimates when comparing truncated to full-population estimators. The mismatch between distributional assumptions and the pattern of observed individual demands was further identified as a problem of “excess zeros” in full population models by Gurmu and Trivedi (1996), Haab and McConnell (1996) and Shonkwiler and Shaw (1996). These authors developed hurdle models based on Mullahy (1986) whereby Poisson and negative binomial specifications include a nonparticipation spike to increase the probability mass on zero demand.

The preceding developments occurred primarily in the context of single-site models. In the multiple-site context, Englin and Shonkwiler (1995) applied a truncated negative binomial estimator in a system of site-demand equations. Herriges, Kling, and Phaneuf (2004) addressed nonparticipation in a multiple-site Kuhn-Tucker model. Like the Tobit model, the Kuhn-Tucker model fits trip demand to a continuous distribution and allows a portion of the distribution to fall below the threshold for positive demand. The Kuhn-Tucker model was combined with a nonparticipation spike in von Haefen and Phaneuf (2003), and the same study also added a nonparticipation spike to a negative binomial demand-system framework. In the repeated-logit context, Morey et al. (1995) noted the difficulty of accounting for a large number of nonparticipants when nonparticipation is represented by a succession of independent no-trip choices. The repeated nested-logit model of participation was updated by von Haefen, Massey, and Adamowicz (2005) to include refinements previously applied to other estimators. A nonparticipation spike augmented the share of zero demands and a randomized no-trip constant added heterogeneity to the demand distribution.

This study examines nonparticipation spikes and demand heterogeneity as tools for addressing nonparticipation in the nested logit context. The results are compared to those of an alternative model more closely related to the underlying choice process that determines participation decisions. In the proposed model, the nested-logit demand function for annual trips is expanded into a distribution of individual demands by randomizing the no-trip constant as suggested by von Haefen, Massey, and Adamowicz (2005). If all individuals in this behavioral model were to be viewed as participants, an estimate of nonparticipation could still be obtained from the mass on zero demand predicted by the binomial-form likelihood function. This is the basic approach used in previous discrete-form models. Instead, the proposed model applies a participation threshold to the distribution of preferences represented by the random no-trip constant. This is similar to continuous specifications such as the Tobit or Kuhn-Tucker models in that the share of nonparticipants can take up any portion of the preference distribution and is not constrained by the parameters of a discrete probability function. Finally, the participation threshold is connected to the behavioral demand model because it corresponds to a choke price on individual demands.

1.2 Model

The proposed model is based on the widely used repeated nested-logit specification for annual demand attributed in the recreation demand literature to Morey, Rowe, and Watson (1993). The site-choice probabilities for site j and individual n are described by:

$$(1) \qquad P_{nj} = \frac{e^{sV_{nj}}}{\sum_j e^{sV_{nj}}}.$$

Site utilities V_{nj} consist of preference parameters β multiplied by x_{nj}, representing prices (travel cost) and site characteristics. The scale parameter s is from the upper-level participation nest. Probabilities for the upper-level nest can be expressed separately from the site-choice probabilities, allowing participation for each of D choice occasions to be collected into a single expression. Annual trip demand T_n is given by:

$$(2) \qquad T_n = D \frac{\left(\sum_j e^{sV_{nj}} \right)^{(1/s)}}{e^{V_0} + \left(\sum_j e^{sV_{nj}} \right)^{(1/s)}}.$$

V_0 is the utility of alternative activities. The number of choice occasions D is selected by the researcher, setting an upper limit on predicted demand for an individual in a season. The scale parameter s helps define the shape of the demand function.

It is useful to distinguish individuals of type i, defined by demographic characteristics, from individual observations n. Participation models are often estimated for a representative agent (e.g., Parsons 2004). That is, all individuals n_i of a given type i are assumed to take trips according the demand function in (2), where V_0 is interacted with demographic variables. There is no mechanism to account for unobserved heterogeneity in annual demand, and no specific distinction between participants and nonparticipants. This restriction can be relaxed by introducing a distribution for V_0 that captures unobserved heterogeneity. A threshold value V_0^* will distinguish those who participate from those who do not. Based on these refinements, the probability of taking a trip for participant n of type i is described by an expectation over $f(V_0)$ truncated at V_0^*. Annual trip demand is given by:

(3) $$E(T_{n_i}) = D \int_{V_0=-\infty}^{V_0^*(l_n)} \frac{\left(\sum_j e^{sV_{nj}}\right)^{(1/s)}}{e^{V_0} + \left(\sum_j e^{sV_{nj}}\right)^{(1/s)}} f(V_0|z_i)dV_0 \,.$$

The preference distribution $f(V_0|z_i)$ is conditional on demographic characteristics z_i, and an observed individual is viewed as a random draw from this underlying demographic group. Note that lower values of V_0 are associated with greater trip demand since the utility of taking a trip is higher by comparison. Expected demand for trips conditional on participation therefore corresponds to the integral over $f(V_0|z_i)$ below V_0^*. The term V_0^* is identified in (3) as specific to a given location l_n because it depends on the proximity of recreation sites as determined by an individual's place of residence. As sites become more distant the threshold for participation is expected to become more restrictive.

Consider the specification of V_0^*. Each draw from $f(V_0|z_i)$ denotes preferences associated with a specific level of consumer surplus obtained from participation. The threshold between participation and nonparticipation occurs at the point of indifference where any costs associated with participation are just offset by the anticipated benefits. If C is the cost of entry, the point of indifference can be expressed using the log-sum formula for consumer surplus in a nested logit:

(4) $$C = D \frac{\ln\left(\left(\sum_j e^{sV_{nj}}\right)^{(1/s)} + e^{V_0^*(l_n)}\right) - V_0^*(l_n)}{\beta_p} \,.$$

The difference in (4) represents the loss of access to all sites. The parameter β_p is the coefficient on travel cost. Rearranging (4) gives:

(5) $$V_0^*(l_n) = \ln\left(\left(\sum_j e^{sV_{nj}}\right)^{(1/s)}\right) - \ln\left(e^{\beta_p C/D} - 1\right).$$

For a licensed activity the cost of entry C must at least include the annual license fee, but it may also be greater than the fee. Note that the standard formula for consumer surplus on the right-hand side of (4) assumes an infinite choke price for annual trip demand. If the choke price in the absence of a license fee is less than infinite, then $C > 0$ without the fee and $C > fee$ when a fee applies. Also note that the choke price varies across individuals because it is defined implicitly by $f(V_0|z_i)$ in addition to the constant C. For two participants facing similar prices, the one with a lower V_0 accepts a greater increase in price before his consumer surplus is reduced to C and he is induced to exit from the activity.

To construct the likelihood function, the probability of taking a trip on a given choice occasion for individual n of type i, conditional on participation, is raised to a power representing the individual's observed trips. An analogous expression describes choice occasions when no trip is taken. The resulting contribution to the likelihood function for annual demand by participant n is:

(6) $$P(T_{n_i}) = \left[\int_{V_0=-\infty}^{V_0^*(l_n)} \frac{\left(\sum_j e^{sV_{nj}}\right)^{(1/s)}}{e^{V_0} + \left(\sum_j e^{sV_{nj}}\right)^{(1/s)}} f(V_0|z_i)\,dV_0\right]^{T_n}$$

$$\times\left[\int_{V_0=-\infty}^{V_0^*(l_n)} \frac{e^{V_0}}{e^{V_0}+\left(\sum_j e^{sV_{nj}}\right)^{(1/s)}} f(V_0|z_i)dV_0\right]^{(D-T_n)} .$$

Participation is defined by the purchase of a license. The probability of buying a license for an individual at location l_n is given by the *cdf* associated with $f(V_0|z_i)$ below the threshold for participation V_0^*:

(7) $$F_i\left[V_0^*(l_n)\right]=\int_{V_0=-\infty}^{V_0^*(l_n)} f(V_0|z_i)dV_0 .$$

Let $b_n = 1$ if individual n bought a license, zero otherwise. License demand for individual n contributes the following term to the likelihood function:

(8) $$P(b_{n_i})=\left\{F_i\left[V_0^*(l_n)\right]\right\}^{b_n}\left\{1-F_i\left[V_0^*(l_n)\right]\right\}^{(1-b_n)}.$$

Finally, recalling (1) let the site-choice probabilities for observed trip t be $P_{nj}^t = P_{nj}$ and let $y_{nj}^t = 1$ if individual n chose site j on trip t and zero otherwise. The likelihood function is given by:

(9) $$\prod_n P(b_n)\prod_{n\in B}\prod_{tj} P(T_n)\left(P_{nj}^t\right)^{y_{nj}^t} .$$

The first product accounts for the license purchase decisions of all individuals in the sample. For subgroup B of individuals who purchased a license, the likelihood function also includes annual demand and site-choice decisions. The likelihood function is maximized over the preference parameters β, the nested-logit scale parameter s, the cost of entry C, and the moments $\overline{V}_{0i}$ and σ_0^2 describing $f(V_0|z_i)$.

1.3 *Application*

The proposed model is applied to a kind of recreational shrimp harvest in South Carolina called shrimp baiting. Shrimp baiting takes place over two months each fall and involves the placement of bait in shallow water to attract shrimp, which are then collected in a net. The primary destinations for shrimp baiting are Beaufort, St. Helena Sound, Edisto Island, Charleston, Bulls Bay, and Georgetown. Shrimp baiting is a licensed activity, and the state administered a survey to license holders in 2002 for monitoring purposes. The survey was sent to a random selection of 3,550 license holders out of a total 13,098 license holders in the state. The response rate was 40.1 percent, yielding a sample of 1,425 people and 5,570 trips. The annual license fee in 2002 was $25.

Preferences $f(V_0|z_i)$ are represented by a normal distribution with mean $\overline{V}_{0i} = \overline{V}_0 + \gamma z_i$ and standard deviation σ_0. The term γz_i captures interactions between the no-trip constant and demographic variables. To focus on model performance with respect to participation rather than the value of particular site characteristics, the utilities for each site are represented by alternative-specific constants. Also, demographic characteristics for nonparticipants are not available on the level of individual observations. Demographic variables therefore enter the model based on zip-code level data available from the U.S. Census (using the Census-designated Zip Code Tabulation Areas). Previous studies that have used aggregate-level variables include Shonkwiler and Englin (2005), Englin, Boxall, and Watson (1998), and Englin and Shonkwiler (1995). The advantages and drawbacks of using aggregate data are discussed in Hellerstein (1995) and Moeltner (2003). An overview of variables used in the model is presented in Table 1.1.

Table 1.1. Sample Summary Statistics[a]

Variable	Units	Average	Standard Deviation	Maximum	Minimum
Distance	Miles	145	69.5	296	1
Median Age	Years	36.6	4.4	56.6	19.7
Median Income	$1,000/Year	34.4	9.6	75.8	9.4
Race = White	% of Population	63.7	22.5	100.0	4.2

[a]Demographic variables represent aggregate figures assigned to respondents by zip code of residence.

Travel cost from an individual's zip code to each of the sites included monetary and time-related costs. Monetary costs were calculated as round-trip distance in miles multiplied by 35 cents per mile, divided by 2.5 to reflect the average number of participants in a vehicle. This estimate of marginal per-mile driving expenses was based on data from the American Automobile Association. Travel time was estimated as distance divided by 40 miles per hour. The cost associated with travel time was valued at one-third the wage rate, following studies such as Train (1998), Parsons, Massey, and Tomasi (1999), and Moeltner (2003). Since most participants in shrimp baiting are men, the wage rate was approximated by the median hourly earnings for South Carolina males.

Model parameters were estimated using maximum simulated likelihood. The site-choice component is simple logit and does not require simulation, and the demand for licenses was estimated using the *cdf* function in GAUSS for a normal distribution. Estimation of the demand for trips required simulation using random draws of V_0 from the tail of a normal distribution. This was accomplished by drawing from a standard uniform density, multiplying each draw by the normal *cdf* $F_i[V_0^*(l_n)]$, then taking the inverse normal *cdf* of the result. Details of this procedure for drawing from truncated univariate densities are given in Train (2003). One thousand draws for each observation were used in estimation. An appendix that reviews the model equations and presents the GAUSS code used in estimation is available in (forthcoming).

1.4 Results

Table 1.2 presents parameter estimates for the proposed "choke price" model along with several others. The site-choice model is simple logit. For the remaining models, let L_{NL} be an individual's contribution to the likelihood function in a simple nested logit based on (1) and (2). The nested logit estimated in Table 1.2 is based on $L_{NL}(z_i)$, where V_0 is represented by $\overline{V_0}$ interacted with demographic variables z_i. The panel random coefficients model expands the nested logit to account for heterogeneity in annual demand by applying a normal distribution to V_0. An individual's contribution to the likelihood function becomes

$$L_P = \int_{-\infty}^{+\infty} L_{NL} f(V_0 | z_i) dV_0 .$$

This form for the nested-logit panel model was estimated previously by von Haefen, Massey, and Adamowicz (2005) and is similar to negative binomial estimators used by Haab and McConnell (1996), von Haefen and Phaneuf (2003), and others.

The hurdle model adds a nonparticipation spike to the nested logit model. An individual's contribution to the likelihood function becomes $L_H = (I_{T=0})\pi + (1 - \pi) L_{NL}(z_i)$. The indicator function equals one when an individual's demand for trips is zero. This expands the share of zero demands by π and also excludes this share of individuals from the behavioral model. A logistic form was used for π with

Table 1.2. Model Parameters

Variable	Site Choice Model		Nested Logit Model		Panel Model		Hurdle Model		Choke Price Model	
Log Likelihood	-6,360		-56,488		-33,467		-39,224		-35,954	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Travel Cost (β_p)	-0.12	(47.6)	-0.12	(46.0)	-0.12	(47.6)	-0.12	(47.6)	-0.12	(47.6)
Beaufort	3.12	(33.9)	3.20	(32.9)	3.16	(33.9)	3.12	(33.8)	3.16	(34.4)
St. Helena	3.29	(33.1)	3.39	(32.1)	3.33	(33.1)	3.29	(33.0)	3.33	(33.5)
Edisto Island	0.95	(10.4)	1.03	(10.7)	0.97	(10.4)	0.94	(10.3)	0.98	(10.8)
Charleston	1.22	(17.0)	1.27	(17.0)	1.24	(17.0)	1.21	(16.8)	1.24	(17.3)
Bulls Bay	2.28	(32.1)	2.31	(30.6)	2.30	(31.9)	2.28	(32.0)	2.29	(32.3)
S	-	-	4.57	(34.9)	3.21	(32.3)	22.09	(9.5)	5.88	(7.6)
$\bar{V}_0$	-	-	9.44	(97.3)	26.94	(72.3)	1.98	(15.5)	11.72	(9.6)
$\bar{V}_0$ X Age	-	-	-0.031	(10.9)	-0.054	(7.0)	0.017	(4.7)	-0.026	(4.5)
$\bar{V}_0$ X Income	-	-	-0.009	(5.6)	-0.045	(15.3)	-0.002	(1.1)	-0.011	(3.5)
$\bar{V}_0$ X Race	-	-	-0.38	(4.0)	0.05	(0.9)	-0.23	(1.9)	-0.13	(0.9)
σ_0	-	-	-	-	7.69	(87.2)	-	-	2.61	(7.6)
Hurdle Dummy	-	-	-	-	-	-	7.54	(41.5)	-	-
Hurdle X Age	-	-	-	-	-	-	-0.57	(11.0)	-	-
Hurdle X Income	-	-	-	-	-	-	-0.32	(12.9)	-	-
Hurdle X Race	-	-	-	-	-	-	1.51	(10.7)	-	-
C	-	-	-	-	-	-	-		64.85	(3.2)

demographic variables z_i entering linearly. This specification is the "double hurdle" form used in von Haefen, Massey, and Adamowicz (2005), von Haefen and Phaneuf (2003), and elsewhere.

As shown in Table 1.2, asymptotic *t*-stats indicate that relevant tests of parameter significance are satisfied in most cases. The exceptions are coefficients on race and income, but since each of these coefficients is significant in at least one model they are retained across all models for consistency. The site constant for Georgetown is set to zero for model identification. In the nested-logit portion of each model, the scale parameter s is greater than one indicating consistency with a well-behaved error distribution.

In the choke-price model, the estimated threshold C is \$65. This appears to at least account for the \$25 cost of a license in the threshold to seasonal participation. The remaining \$40 further defines the appropriate choke price for individual demands. By combining equations (5) and (2) with the parameters in Table 1.2 it can be shown that demand is 1.3 trips per year at the choke price implied by C. This represents the minimum level of demand that induces the purchase of a license. For comparison, the average number of trips per license holder in 2002 was 3.9 trips per year.

A selection of results from the four models is presented in Table 1.3. Many of the calculations are based on standard nested logit formulas for demand and consumer surplus, with nonparticipation represented by the probability mass on zero demand. Panel model results are calculated by averaging nested logit formulas over 1,000 draws from the distribution of the no-trip constant. Hurdle model estimates are calculated as $(1-\pi)$ multiplied by the nested logit formulas, following Haab and McConnell (1996) and von Haefen and Phaneuf (2003). Choke-price model results for demand and consumer surplus use nested logit formulas averaged over 1,000 draws of V_0 below V_0^*. The cost C is subtracted from the nested-logit estimate of consumer surplus for each participant. Nonparticipation for the choke-price model is represented by $\{1 - F_i[V_0^*(l_n)]\}$ and license revenue is the license fee multiplied by the number of participants.

The predictions of the choke-price model are statistically indistinguishable from actual figures for both total trip demand and number of participants. The nested logit accurately predicts total trips, but significantly overestimates the number of participants. The correction for overdispersion in the panel model and the nonparticipation spike in the hurdle model generate modest improvements in the predicted number of participants compared to the nested logit model. However, the estimates are still dramatically higher than the actual figures, with *p*-values less than 0.001 in both cases. Furthermore, the panel and hurdle models significantly overstate total trip demand, suggesting that estimates of consumer surplus are likely to be biased.

Additional results are examined for two resource changes: a closure of the Bulls Bay site, and a resource improvement at Bulls Bay. The resource improvement is generated by increasing the site constant for Bulls Bay by an amount equivalent to \$10 per Bulls Bay trip. Such an improvement could represent, say, an increase in catch rates or an improvement in water quality (e.g., Morey, Rowe, and Watson 1993; Jakus et al. 1997). The changes in total trip demand and consumer surplus predicted by the choke price model are statistically identical to those of the nested logit model. Note that nested logit estimates of consumer surplus are unbiased if the conditional mean of demand is correctly specified (Hellerstein and Mendelsohn 1993). By contrast, the welfare effects predicted by the panel and hurdle models are both significantly higher.

Table 1.3. Comparison of Model Predictions

	Actual	Nested Logit Model		Panel Model		Hurdle Model		Choke Price Model	
Baseline conditions									
Total consumer surplus ($)	-	1,937,688	(40,698)	14,619,591	(392,091)	16,778,074	(1,950,124)	1,899,633	(106,590)
Total trip demand[a]	51,244	51,240	(669)	235,151	(2,937)	88,416	(2,566)	50,821	(1,677)
Total number of participants	13,098	50,566	(652)	21,293	(310)	20,365	(440)	13,098	(485)
Total license revenue ($)	327,450	-	-	-	-	-	-	327,445	(12,133)
Site closure at Bulls Bay									
Change in consumer surplus ($)	-	-130,239	(4,400)	-591,930	(20,432)	-201,208	(8,640)	-130,479	(5,968)
Change in trip demand	-	-3,443	(134)	-8,510	(347)	-1,017	(112)	-3,269	(210)
Change in number of participants	-	-3,364	(130)	-699	(30)	-13	(3)	-765	(44)
Change in license revenue ($)	-	-	-	-	-	-	-	-19,120	(1,089)
Quality improvement at Bulls Bay									
Change in consumer surplus ($)	-	181,962	(4,372)	794,522	(17,804)	266,301	(8,844)	180,377	(6,986)
Change in trip demand	-	4,811	(145)	11,625	(363)	1,345	(141)	4,487	(278)
Change in number of participants	-	4,683	(139)	944	(32)	17	(3)	1,039	(55)
Change in license revenue ($)	-	-	-	-	-	-	-	25,973	(1,381)
Increase in license fee from $25 to $35									
Change in consumer surplus ($)	-	-	-	-	-	-	-	-119,942	(5,072)
Change in trip demand	-	-	-	-	-	-	-	-2,741	(132)
Change in number of participants	-	-	-	-	-	-	-	-1,960	(279)
Change in license revenue ($)	-	-	-	-	-	-	-	62,383	(10,816)

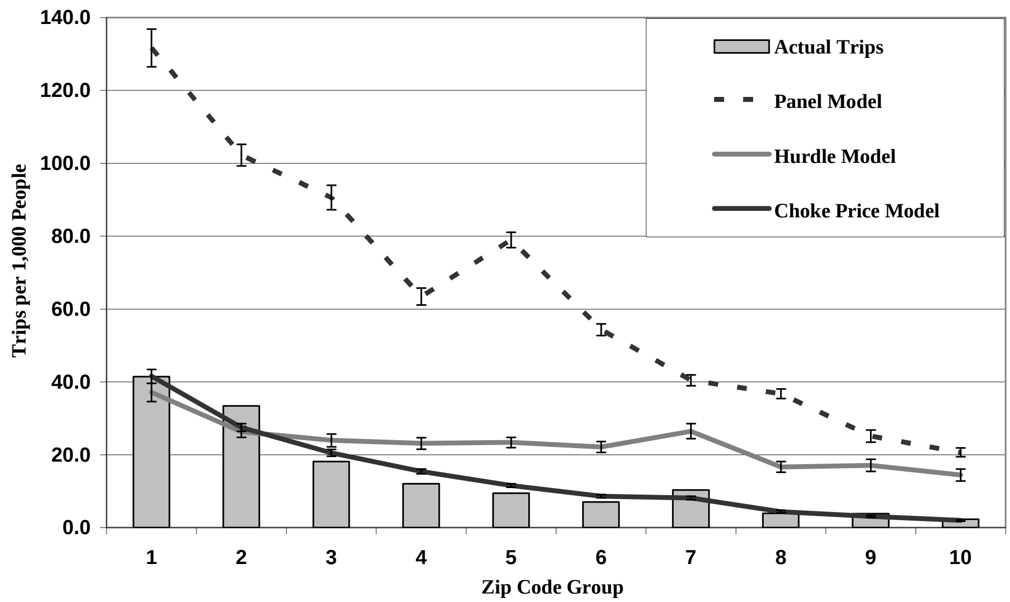
Note: Standard errors appear in parentheses based on a parametric bootstrap procedure using 500 draws. Welfare estimates are in 2002 dollars.

[a]The estimate of actual total trip demand is extrapolated from the sample, with a standard error of 1,522.

Table 1.3 also shows the predicted effects of an increase in the license fee from \$25 to \$35. The choke price model is capable of generating these predictions because an increase in the license fee can be expressed as a change in the choke price on individual demands. While the \$10 fee increase generates additional revenue, the loss in welfare accruing to consumers is greater than the gain in revenue. These final results should be viewed with caution because the data do not contain variation in license fees from which this effect can be directly estimated. However, as in all the scenarios presented, changes in license revenue represent a potentially important component of the value of resource use that is typically ignored in recreation demand studies.

To evaluate the performance of a travel-cost model it is important to understand the success of the model in estimating the demand response to price. Figure 1.1 compares the demand predictions of the panel, hurdle and choke-price models to actual figures across geographic space. To facilitate the analysis, zip codes are assembled into groups sorted by declining inclusive value (*IV*) as estimated by the site-choice model in Table 1.2. The inclusive value statistic is part of the nested-logit structure in all three models in Figure 1.1 and can be viewed as a price index for access to sites (Hausman, Leonard, and McFadden 1995; Parsons, Jakus, and Tomasi 1999). Put simply, if an access fee Δp is imposed at all sites then the nested logit formula requires that $(IV_{\Delta p} - IV_0) / \beta_p = \Delta p$, where subscripts Δp and 0 indicate that the inclusive value does or does not include the access fee, respectively. The relationship between the inclusive value and demand is important to welfare estimation, because integrating annual trip demand over a change in the inclusive value (or Δp) generates the standard log-sum consumer surplus formula that appears in (4), as described in McConnell (1995).

It is clear from Figure 1.1 that predicted demand for the panel model on average declines more quickly than actual demand across the 10 zip code groups. In the hurdle model, changes in predicted demand are considerably smaller than changes in actual demand across most of the observed range. Bias in the demand response to price in these models is likely to correspond to bias in welfare estimates for a resource change. The choke price model appears to perform considerably better. While some smoothing is evident, both the trend and total level of predicted demand are reasonably close to the actual figures. The predictions of the nested logit are not included in the figure but are nearly identical to those of the choke price model.

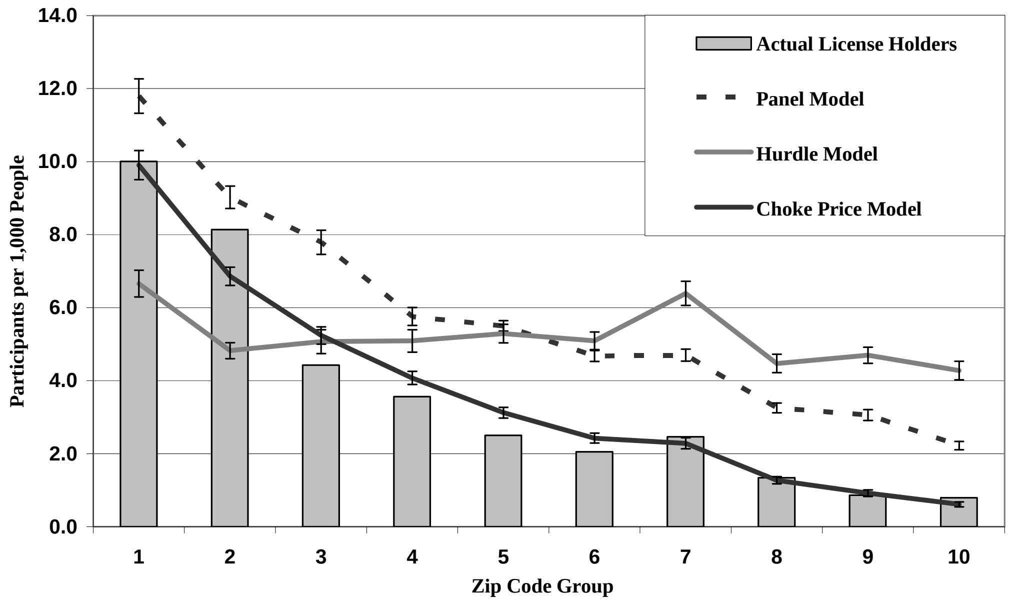


Note: Error bars indicate 95-percent confidence intervals based on a parametric bootstrap procedure using 500 draws.

Figure 1.1. Comparison of trip demand predictions.

Figure 1.2 shows the number of participants per 1,000 people based on the same zip code groups as Figure 1.1. In the panel model, the predicted number of individuals with positive demand consistently exceeds the number of licenses purchased. Since 22 percent of license holders in fact had zero trip demand, the panel model predictions would fare even worse in a direct comparison to active participants.

In the hurdle model, a muted response to price is again evident in the very modest decline in predicted participation across space. The choke-price model captures observed behavior reasonably well, with respect to both the response to price and the total number of participants.



Note: Error bars indicate 95-percent confidence intervals based on a parametric bootstrap procedure using 500 draws.

Figure 1.2. Comparison of participation predictions.

1.5 Conclusions

Allowing for heterogeneity in individual demands is a common approach to addressing nonparticipation in discrete-form models. One difficulty with this approach is the potential for bias in predictions of total demand. Instructive examples include Gillig, Ozuna, and Griffin (2000) and von Haefen and Phanuef (2003) who, respectively, identified significant underprediction and overprediction of demand using negative binomial estimators. Bias in demand predictions was also evident in the panel nested logit estimated for this study, which introduced heterogeneity in annual demand using a normal distribution for the no-trip constant. These and other related specifications rely on a behavioral model that treats all individuals as participants, in the sense that expected demand is constrained to be positive over the entire range of preferences. The model developed in this study divides the preference distribution into participants and nonparticipants by incorporating nonparticipation into the behavioral model. A choke price defines each individual's participation threshold, and demand is estimated conditional on the choice to participate. The proposed model produced reasonable estimates of both nonparticipation and trip demand, and an examination of the demand response to price supported the validity of corresponding welfare estimates.

A nonparticipation spike is often used to augment the share of zero demands in nested-logit or negative binomial models. Like the choke price model, the resulting hurdle model uses a distribution of preferences to distinguish participants and nonparticipants and may improve predictions when the share of zero demands exceeds what is accommodated by a parametric discrete-form probability function. However, the hurdle model imposes for the share π of nonparticipants a class of preferences that precludes any behavioral response to price or resource characteristics. This form for preferences may seem like an implausible approximation (Phaneuf and Smith 2005). It may also limit the ability of the model to accommodate observed changes in behavior. In the example estimated for this study, the exclusion of the share π from the behavioral model appeared to create significant attenuation in the demand response to price.

For South Carolina shrimping, accurate predictions of the number of participants were useful for estimating changes in license revenue. Standard nested logit nets out license fees and other costs to the consumer because the representative-agent function for demand is analogous to a market-level demand curve. In models that estimate individual-specific demands without an explicit choke price, the treatment of license fees is less clear. One could argue that value generated by the use of a resource should not be ignored simply because it has been transferred from the consumer to the licensing authority. For the resource changes examined in this study, accounting for changes in license revenue would increase welfare estimates by approximately 15 percent. Total license fees in the U.S. for fishing and hunting alone amount to over $1 billion (U.S. Fish and Wildlife Service 2002) suggesting that conventional models may be ignoring a significant portion of the value of recreational use.

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CHAPTER 2:

ANNUAL FEES AND RECREATION CHOICE

In most recreation demand models the source of information about preferences is data on recreation trips. Demand for trips is regressed on trip prices and site characteristics to obtain estimates of preference parameters. A problem may arise if consumer choices are influenced by annual fees in addition to per-trip prices. For example, coastal towns in Massachusetts each sell a separate recreational license for access to local shellfish beds and annual license fees vary across towns by $100 or more. A researcher may wish to examine shellfishing demand and substitution throughout the region, but a multiple-site model of recreation trips would fail to account for the annual fees and would falsely ascribe the reduced demand in high-fee towns to local resource characteristics. Methods applied in the recreation demand literature typically ignore the role of fixed fees and cannot address this type of situation.

Motivated by this problem we develop a discrete-choice random-utility model that accounts for the influence of annual user fees on recreation behavior. The utility of purchasing a license at a given site depends on the value of trips to the site, which is a function of trip prices and site characteristics. Utility accounts for the influence of annual fees because consumers evaluate a tradeoff between the cost of a recreational license and the value of recreation trips. The model combines techniques commonly used in recreation demand with methods drawn from the literature on discrete-continuous choice and two-part tariffs.

The model may be of interest in several respects. First, we show that the consumer response to both annual fees and per-trip prices can be combined in a consistent model of recreation behavior. The approach we develop may be applied to other recreation-demand problems in which fixed annual expenses play an essential role in consumer choice, for example, the purchase of a season pass at a ski area, the selection of a marina by recreational boaters, or the purchase of a house that affords access to local recreation amenities. Second, our study represents a new application of recent advances in modeling recreation participation. Specifically, English (2008) extended random-utility models of site choice and annual trip demand to account for the choice whether to participate in a recreational activity. We find that similar modeling techniques are useful in addressing site-specific fees, which present the consumer with the analogous choice of whether to participate in recreation at a particular site. Third, we compare welfare measures based solely on value that accrues to consumers with welfare measures that account for value transferred to the government in the form of license fees. Our approach is more consistent with the literature addressing other economic choices governed by a two-part structure of fixed and unit prices, and may be appropriate for the analysis of resource policies in many cases.

2.1 Background

The use of random-utility models to examine the choice of outdoor recreation sites has a long provenance. A summary of the major developments is presented in Herriges and Kling (2003) and Phaneuf and Smith (2005). To our knowledge the role of annual fees in recreation choice has been previously addressed only in English (2008), which examined consumer behavior in the presence of a statewide license fee for a particular recreational activity. Our analysis of fixed fees specific to particular sites requires a different modeling approach, though we adopt some elements of English (2008), as described below. Another instructive precedent in the recreation demand literature involves repeated-logit models, first developed by Morey, Rowe, and Watson (1993) and later applied in numerous studies (e.g. Montgomery and Needelman 1997;

Parsons, Jakus, and Tomasi 1999; MacNair and Desvousges 2007). While our model bears little theoretical relationship to repeated-logit analysis, we adopt the logistic specification for demand implicit in the repeated-logit model because it has desirable properties for the analysis of recreation trips.

Aside from these examples, the techniques we draw upon for the methods proposed in this article were primarily developed outside the field of recreation demand. The topics most important to our analysis include discrete-choice methods based on random-utility maximization, the extension of discrete-choice analysis known as “discrete-continuous choice”, and “two-part tariff” models evaluating choice and welfare when prices involve both fixed and variable components.

In models based on random utility maximization, an individual’s choice among discrete alternatives is described by conditional indirect utilities associated with each alternative (McFadden 1974). Conditional indirect utilities define the maximum utility an individual can achieve conditional on the choice of a given alternative. Utility depends on characteristics of the alternatives as well as factors specific to the individual. Some of the individual-specific factors are not observed by the researcher, so conditional indirect utilities are specified to include a random component drawn from a population-level distribution of preferences. Choice probabilities are estimated by integrating the individual’s utility decision rule over the population-level preference distribution to identify the portion of the distribution associated with the choice of each alternative. This general approach is common to all random-utility models and is reviewed in detail by Train (2003).

The purchase of a recreational license combined with the decision of how many trips to take is similar to other choices that occur in two related stages, and may be viewed in the context of “discrete-continuous” models. These models use conditional indirect utilities to describe the discrete first-stage choice, combined with a continuous function that predicts the quantity demanded of the second-stage good (Dubin and McFadden 1984; Hanemann 1984). The demand response to price in the second stage of the model is related by Roy's identity to indirect utility in the first stage of the model.

In discrete-continuous models, first-stage choices may be determined in part by characteristics of the first-stage good (Train 1986; Bento et al. forthcoming) or may be determined solely by the fee for the first-stage good combined with prices and characteristics of the second-stage good (Miravete 2002; Narayanan, Chintagunta, and Miravete 2007). Our model takes the second of these two approaches, since a recreational license is likely to have no features of interest other than the license fee and access to recreation trips.

Consumer choice in the presence of both fixed fees and unit prices has been widely investigated in the literature on two-part tariffs. Oi (1971) used Disneyland as an example and analyzed the profit-maximizing combination of an entrance fee for the park and a unit fee for rides. Subsequent articles have addressed two-part tariffs in the context of profit maximization for firms setting prices or optimization of social welfare for governments setting tax policy (Schmalensee 1981; Train, Ben-Akiva, and Atherton 1989; De Borger 2000). Throughout this literature, consumers evaluate a tradeoff between fees for access to a particular good and value derived from consuming the good, where total value from the researcher's point of view includes both value accruing directly to consumers as well as value associated with the fixed fees. The model below extends the analysis of recreation choice to account for fixed fees in a similar manner.

2.2 Model

The model is developed in the context of random utility maximization (McFadden 1974; Train 2003). Let utilities $\{V_{nj}\}$ describe license-purchase decisions, where n denotes individuals in the population and j denotes alternatives $j \in J + 1$. There are J sites where a license can be purchased and the choice not to purchase a license is denoted by $j = 0$. With nonparticipation captured in V_{n0}, the choice alternatives are exhaustive, as required by random-utility theory. We also assume that choice alternatives are mutually exclusive, which is the second requirement of random-utility models. While not strictly true for the shellfishing problem analyzed below, we believe this assumption is innocuous as an empirical matter because no individuals were identified who purchased a license in more than one location. Let $V_{n0} = y$ where y is annual income, and let utility for purchasing a license at each of the sites be described by the function

$$(1) \qquad V_{n,j>0} = D\frac{\ln\left(e^{\alpha p_{nj}+\eta_{nj}+\theta_n+\beta_y y}+1\right)}{-\alpha} - c - L_{nj} + y\,.$$

For individual n, the utility of choosing site j depends on a scalar D, to be explained below; the price of travel to the site p_{nj} multiplied by a price coefficient α; individual tastes for site j represented by η_{nj}, which may be composed of a vector of site characteristics multiplied by taste parameters; an individual taste shifter θ_n common to all sites, which will assist in model estimation; personal income y multiplied by a coefficient β_y, representing the sensitivity of shellfishing demand to income; a choke constant c, to be explained below; and the annual license fee L_{nj}. Both prices and license fees include the subscript n because they vary by an individual's place of residence (in the application below, license fees in coastal towns differ for residents and nonresidents).

The first term in expression (1) represents utility associated with recreation trips to site j. The functional form is derived from repeated-logit models, as described below. The utility of recreation trips depends on travel costs, tastes for particular shellfishing sites, tastes for shellfishing generally, and income. The utility of site j also depends on the license fee L_{nj}, which is traded off directly with income. The term c represents costs associated with shellfishing not accounted for in travel costs or license fees, such as the cost of acquiring skills or equipment. Alternatively, c can be viewed as a shifter for utility associated with the choke price on recreation trips. Without c, expression (1) would imply that all individuals derive value from shellfishing trips whenever the license fee is zero. This is because the first term in (1) is always positive at any price, implying that demand for shellfishing trips has an infinite choke price. A positive c corresponds to a choke price that is less than infinite and allows for the possibility that some people would choose not to participate in shellfishing even in the absence of a license fee.

Expression (1) ranks the $J + 1$ alternatives, including the J sites and nonparticipation, and each individual n selects her highest-utility option. If the utility derived from shellfishing trips offsets the cost of a license for at least one site, the individual chooses to purchase a shellfishing license. When several sites are preferred to nonparticipation, the individual chooses the site offering the highest utility.

The motivation behind the functional form in expression (1) is its relationship to functional forms common in the recreation demand literature and its desirable properties in the context of recreation behavior. Specifically, we derive the demand for trips conditional on the choice of site j by applying Roy's identity to indirect utility in expression (1). An individual's trip demand to site j, calculated as $q_j = (\partial V_j/\partial p_j)/(\partial V_j/\partial y)$, is given by

(2) $$q_{n,j>0} = D\frac{e^{\alpha p_{nj}+\eta_{nj}}}{e^{\alpha p_{nj}+\eta_{nj}} + e^{-\theta_n - \beta_y y} + \beta_y D\frac{e^{\alpha p_{nj}+\eta_{nj}}}{\alpha}}.$$

In the absence of income effects ($\beta_y = 0$) expression (2) is the logistic demand function for trips to a single site as estimated in a repeated-logit model (Morey, Rowe, and Watson 1993; Morey 1999). In the context of repeated logit, the utility of site *j* would be $\alpha p_{nj} + \eta_{nj}$ and the utility of alternative activities would be $-\theta_n$. The scalar *D* would represent choice occasions, and would be set high enough to accommodate a reasonable upper limit on trips in a season. The logistic demand function is the most common functional form applied in the recreation-demand literature, given the prevalence of random-utility logit models (Phaneuf and Smith 2005). Expression (2) is also related to the commonly used semi-log demand function, which is a special case of (2) with *D* selected to be a large number (Hellerstein and Mendelsohn 1993; Parsons, Jakus, and Tomasi 1999).

For our purposes it is desirable to take advantage of a finite *D* as a reasonable upper bound on predicted trips so that the demand function in (2) incorporates satiation in annual demand. Below we allow individual demand to vary according to a preference distribution, and functional forms that ignore satiation in individual demand allow for extremely large predictions of demand and consumer surplus for some individuals. We allow variation in tastes for recreation trips because it is essential to a model that accounts for the choice whether to participate in a recreational activity. In general, satiation in demand is a realistic feature for recreation demand models because time constraints place an upper limit on trip demand regardless of individual income.

To complete derivation of the shellfishing model in the context of random utility maximization, we assume that variation in preferences across people is partly associated with observed demographic variables and partly associated with individual-specific factors unobserved to the researcher. The unknown portion of an individual's utility must be represented by a probability density corresponding to the population-level distribution of tastes. One approach would be to include an additive extreme-value error term in (1), following Dubin and McFadden (1984) and other discrete-continuous specifications such as Train (1986) and Bento et al. (forthcoming). This would result in the familiar closed-form logit choice probabilities for the purchase of a license. However, an additive error term would suggest that different consumers prefer one site over another for reasons unrelated to the remaining terms in the utility function, that is, unrelated to utility from recreation trips. We instead follow the common practice in recreation demand and assume that preference heterogeneity is associated with the utility of site visits, as captured by the parameters θ and η in (1) and (2). Specifically, a preference distribution $f(\theta)$ captures heterogeneity in the demand for shellfishing, that is, heterogeneity in demand for trips to any of the J sites relative to alternative activities. The J-dimensional preference distribution $f(\eta)$ captures heterogeneity in preferences for specific sites.

Probabilities associated with an individual's choices are calculated by integrating the utility-based decision rule over the preference distribution represented by $f(\theta)$ and $f(\eta)$. Selection probabilities for the available alternatives, including nonparticipation, are given by

$$(3) \qquad P_{nk} = \int_{\theta=-\infty}^{\infty} \int_{\eta_1=-\infty}^{\infty} \cdots \int_{\eta_J=-\infty}^{\infty} I[\max_j \{V_{nj}\} = V_{nk}] f(\theta) f(\eta) d\eta_1 \ldots d\eta_J d\theta .$$

For any realization of θ and η, the indicator function takes a value of one if alternative k is the highest-utility option. Integrating the indicator function over the distributions

$f(\theta)$ and $f(\eta)$ identifies the portion of the probability distribution associated with choice k, which is equivalent to P_{nk}.

2.3 Data

The shellfishing license data consist of license purchases in 2004 by town of residence for 11 shellfishing sites. The data were compiled from materials provided by state and local resource management officials. Ten of the sites are towns along the southeastern shore of Massachusetts from Scituate south, excluding Marshfield, Fairhaven and Cape Cod. The eleventh site is the state of Rhode Island. Scituate is the first location south of Boston where recreational shellfishing is allowed. Marshfield did not allow shellfishing in 2004 and data for the town of Fairhaven could not be obtained. Cape Cod was not included in the analysis because it is geographically distinct from the mainland sites. Trips to Cape Cod sites by residents of the mainland are likely to involve a large number of multiple-day trips which would complicate the analysis.

An overview of license purchases and fees is presented in Table 2.1. Sites are listed geographically from north to south. A total of 6,225 licenses were purchased for the 11 sites. Residents of a town where shellfishing is permitted pay a lower license fee than non-residents, and senior residents (over 65) pay the lowest fees. Rhode Island is included in the model to account for choices available to Massachusetts residents, but license purchases by Rhode Island residents are not included in the data. Points of origin in the travel-cost analysis include all Massachusetts municipalities east of Worcester and south of Boston, excluding Cape Cod. This amounts to 127 cities and towns, and license purchases from this region account for all but 22 of the 6,225 licenses in the data. This region also includes 15 towns where no one purchased a license. Participants in shellfishing include anyone who purchased a license in 2004, and the number of nonparticipants is calculated by town of origin as total population less license holders.

No survey was conducted for this analysis and demographic variables enter the model as aggregate-level data obtained from public sources. Specifically, all residents of the region are assigned demographic characteristics based on average statistics for their town of residence. Town-level data are not available from the U.S. Census and were instead obtained from the Massachusetts Institute for Social and Economic Research and a statistical guide to Massachusetts towns published by the New York Times Company. Demographic variables include median household income divided by $10,000 (“income”), the percentage of adults with a college degree (“education”) and the percentage of households with children under 18 (“kids”). Previous studies that have used aggregate-level variables include Englin and Shonkwiler (1995), Englin, Boxall, and Watson (1998), and Shonkwiler and Englin (2005). Some advantages and drawbacks of using aggregate data are discussed in Hellerstein (1995) and Moeltner (2003).

Travel distances were measured from each town of origin to each of the 11 sites. Round-trip distances were converted to prices at a rate of $0.341 per mile per person based on marginal driving expenses estimated by the American Automobile Association and one-third average hourly earnings for Massachusetts households as reported by the U.S. Census. Estimating the time-cost of driving using some variant of one-third the wage rate originated with Cesario (1976) and follows studies such as Train (1998), Parsons, Plantinga, and Boyle (2000) and Moeltner (2003).

Table 2.1. License Purchases and Fees for Shellfishing Sites

Shellfishing Site	License Purchases				License Fees ($)		
	Non-Residents	Residents[a]	Seniors	Total	Non-Residents	Residents[a]	Seniors
Scituate	14	65	59	138	50	20	0
Duxbury	548	422	137	1,107	100	20	0
Kingston	67	109	54	230	55	25	10
Plymouth	18	539	155	712	50	10	0
Wareham	172	984	359	1,515	120	30	15
Marion	100	283	65	448	120	25	0
Mattapoisett	186	350	232	768	120	25	0
New Bedford	3	143	101	247	50	12	3
Dartmouth	13	207	123	343	75	15	0
Westport	65	477	129	671	100	25	10
Rhode Island[b]	46	-	-	46	200	-	-
Total	1,232	3,579	1,414	6,225	-	-	-

[a] "Residents" refers to local inhabitants below the age of 65. "Senior" residents are 65 and older.

[b] License purchases are not reported for residents of Rhode Island because the target population for the study consists of Massachusetts residents only.

We focus only on access value for sites so our data does not include information on site characteristics. The taste distribution for sites will therefore be estimated using J alternative-specific constants to represent the J means of $f(\eta)$. Estimating the value of site characteristics would require replacing the alternative-specific constants with the product of site-specific variables and estimated coefficients. It is possible that site characteristics would provide some information about the value of sites that is not available from observed choices alone. However, most authors suggest that observed choices provide the best information on the utility of choice alternatives and that any mismatch with information on site characteristics results from the failure to adequately measure site characteristics (Hausman, Leonard, and McFadden 1995; Morey and Waldman 2000; Train, McFadden, and Johnson 2000; Murdock 2006). The use of alternative-specific constants is therefore well suited to estimating the value of shellfishing.

2.4 Estimation

It would be possible to estimate the shellfishing model using equations (1) and (3). Repeated draws would be taken from $f(\theta)$ and $f(\eta)$ for each individual in the sample. Utilities V_{nj} would be calculated for each draw using equation (1), with $V_{n0} = y$. For a given draw, the highest value of V_{nj} would identify the selected alternative from among the $J + 1$ options. This process would be repeated for multiple draws. The number of draws corresponding to individual n's choice of alternative k divided by the total number of draws for individual n gives the predicted probability P_{nk}. Probabilities could then be fit to observed choices using maximum likelihood estimation. This type of procedure is called an "accept-reject" simulator and is described in Train (2003).

The number of draws required for estimation can be reduced dramatically by eliminating a portion of the distribution $f(\theta)$ prior to simulating choice probabilities.

Specifically, we know that a large portion of the support of $f(\theta)$ must correspond to the choice not to participate. This is because θ represents variation in the utility of access to any shellfishing site, that is, variation in avidity for shellfishing. A large portion of this distribution will be taken up by the great majority of people in southeastern Massachusetts who do not purchase a shellfishing license. Following English (2008), the portion of the distribution corresponding to nonparticipation can be estimated analytically using the cdf of θ.

First, we find the threshold value of θ associated with an individual's decision to participate at a given site j. For a given draw of η_{nj} at site j, we set $V_{nj} = y$ in equation (1) and solve for θ^*:

$$\text{(4)} \qquad \theta^*(\eta_{nj}) = -\alpha p_{nj} - \eta_{nj} - \beta_y y + \ln\left(e^{-\alpha(c+L_{nj})/D} - 1\right).$$

At θ^* utilities V_{nj} and V_{n0} are both equal to y, so the individual is indifferent between choosing site j and choosing nonparticipation. Given the functional form of (1), values of θ below θ^* are associated with nonparticipation. The threshold where at least one of the J sites is preferred to nonparticipation is given by

$$\theta^*(\eta_n) = \min_j\left\{\theta^*(\eta_{nj})\right\},$$

where η_n is a J-dimensional vector. Using θ^* defined over all J sites as a participation threshold, the estimation of choice probabilities requires simulation techniques only over the portion of $f(\theta)$ consistent with positive demand for a license. Nonparticipation will be estimated using the cumulative distribution of $f(\theta)$ below θ^*, that is, $F[\theta^*]$.

Following a practice common in models of recreation participation, we assume that observed demographic variables z_n enter the model through their influence on total demand for shellfishing trips. The mean of $f(\theta)$ is therefore interacted with z_n

such that $\overline{\theta}_n = \overline{\theta} + \beta_z z_n$, where $\overline{\theta}$ and β_z are estimated. In discrete-choice analysis, taste distributions represented by a single site-specific error term typically take a logistic or normal form. We use a normal distribution for $f(\theta)$ and $f(\eta)$, with standard deviations σ_θ and σ_η. Simulation of the choice probability P_{nk} using an accept-reject simulator proceeds as follows:

1. For each observation take R draws from $f(\eta)$ and from $f(\theta|z_n)$ above θ^*, where θ^* is conditional on each of the draws from $f(\eta)$. Each of the R draws has $J + 1$ dimensions, reflecting the J sites associated with $f(\eta)$ and the nonparticipation alternative associated with $f(\theta|z_n)$.
2. For each draw r set $I_{nk}^r = 1$ if

$$\max_j \{V_{n,j>0}\} = V_{nk}.$$

Otherwise, set $I_{nk}^r = 0$. Utility V is calculated using expression (1). Alternatively, use logit smoothing to insure that step 4, below, never results in a zero probability for any choice outcome. This would require setting

$$I_{nk}^r = e^{V_{nk}/\lambda} \Big/ \sum_{j=1}^{J} e^{V_{nj}/\lambda}$$

for all k from 1 to J, where λ is set as small as possible without creating difficulties in estimation. The result is that I_{nk}^r is close to one for the highest-utility site and is small but nonzero for all other sites (for details see Train 2003).

3. Each I_{nk}^r describes an outcome that is conditioned on participation, because the draw of θ used to calculate utilities was above θ^*. Remove the conditioning by calculating $\{1 - F[\theta^*]_n^r\}\, I_{nk}^r$, where $F[\theta^*]_n^r$ is the cumulative distribution of $f(\theta|z_n)$ up to θ^* for draw r.

4. Calculate

$$P_{n,k>0} = \sum_r \left\{1 - F[\theta^*]_n^r\right\} I_{nk}^r \,/\, R.$$

5. Calculate

$$P_{n0} = 1 - \sum_{k=1}^{J} P_{nk} \; .$$

We used logit smoothing in step 2 and found that λ could be set small enough so that changes in λ appeared to have no significant effect on the estimated parameters.

The form for the likelihood function is

$$\prod_{nj} \left(P_{nj}\right)^{y_{nj}} \; ,$$

where observation $y_{nj} = 1$ if individual n chose alternative j and zero otherwise. The likelihood function was estimated over all alternatives and all individuals, including both participants and nonparticipants. For each site given each town of origin, P_{nj} was estimated using 2,000 random draws from $f(\eta)$ and from $f(\theta)$ above θ*.

2.5 Results

This section presents results of a model in which site-specific error terms η_{nj} are independently and identically distributed. The assumption of independent error terms is sometimes criticized in the context of discrete choice analysis because it imposes restrictive substitution patterns (Train 1998; Layton 2000). Extensions that include more general distributions for $f(\eta)$ were also investigated and the results are available from the author. The simple specification presented here is sufficient to illustrate the performance of the model.

The estimated parameters are reported in Table 2.2. The travel-cost parameter is negative and significant. Site constants $\bar{\eta}_j$ reflect average tastes for site-specific characteristics in each of the shellfishing towns. The most desirable sites for shellfishing are Duxbury, Wareham, Marion, Mattapoisett, Westport and Rhode Island. The site constant for New Bedford is fixed at zero for model identification. The standard deviation of site preferences (σ_η) is smaller than the standard deviation of θ (σ_θ), suggesting that substitution is greater among shellfishing sites than between shellfishing and nonparticipation.

Table 2.2. Model Parameters

Variable	Estimate	St Err
Travel cost (α)	-0.021	(0.001)
Scituate ($\bar{\eta}_j$)	0.267	(0.017)
Duxbury	1.019	(0.008)
Kingston	0.480	(0.011)
Plymouth	0.375	(0.006)
Wareham	1.127	(0.012)
Marion	0.920	(0.013)
Mattapoisett	1.032	(0.012)
Dartmouth	0.469	(0.013)
Westport	0.913	(0.006)
Rhode Island	1.398	(0.018)
St. Dev. of site utilities (σ_η)	0.195	(0.005)
Utility of shellfishing ($\bar{\theta}$)	-5.980	(0.058)
St. Dev. of θ (σ_θ)	0.647	(0.012)
Choke constant (c)	41.00	(10.30)
Income (β_y)	-0.065	(0.004)
Education x $\bar{\theta}$	0.727	(0.080)
Kids x $\bar{\theta}$	0.699	(0.099)
Log likelihood	-33,109	

The mean of the taste distribution for shellfishing trips $\bar{\theta}$ is negative and considerably larger in absolute value than the site constants. Given the logistic demand function in (2), this indicates that most individuals take considerably fewer than D trips in a year. Note that for estimation D was set to 60, providing a reasonable upper bound on annual trip demand based on information from resource managers in Massachusetts. The estimated choke constant c determines the choke price on individual demands absent a license fee. Using equations (1) and (2) it is possible to show that demand at the choke price associated with c is 0.82 trips per year. This can be interpreted to mean that absent a license fee, individuals who are just indifferent between shellfishing and nonparticipation would take a little less than one trip per year on average. The coefficient on income is negative, indicating that shellfishing is an inferior good and that all else equal those with higher income are less likely to purchase a shellfishing license. Those with a college education and those with children under the age of 18 are more likely to engage in shellfishing.

Model predictions appear in Table 2.3. Predictions of total license demand for each site correspond reasonably well to data on actual purchases. A comparison to Table 2.1 shows that nonresident license purchases are somewhat under-predicted for Duxbury and over-predicted for most other sites. For all sites combined, nonresident licenses are overestimated by 18 percent, resident licenses are underestimated by 6 percent, and senior licenses are underestimated by less than one percent. Total license demand is predicted almost exactly.

Table 2.3 also reports figures for predicted trips per license. The model does not use data on trips, but as a way of evaluating model results expected trip demand can be estimated using the equation (2) integrated over the distribution of preferences for shellfishing participants. Estimates range from 1.2 trips per license in New Bedford to 6.8 trips per license in Rhode Island. For all sites combined, average predicted trip demand is 2.1 trips per license. These estimates are similar to actual demand according to local officials at some sites, while officials at other sites indicate demand may be higher. While information on the actual demand for trips could be incorporated into the model, it is not clear that this would result in more valid estimates of willingness to pay for access to shellfishing sites. Willingness to pay is ultimately based on expected behavior, as illustrated by the inevitable occurrence where some consumers pay for a license but fail to take any trips.

The consumer value of shellfishing sites is estimated as equivalent variation (EV) using the expressions for utility given by equation (1). Specifically, conditional on draws of θ_n and η_n, we close a given site j by setting η_{nj} equal to a large negative number. We reevaluate utility based on the new maximum V_{nj}, and a numerical procedure then calculates EV starting with the original value of η_{nj} and searching for the income adjustment that achieves the same change in utility as the site closure. The change in utility would either be zero or negative, depending whether the individual chose the affected site initially given θ_n and η_{nj}. For each type of individual as defined by town of origin, EV is calculated using an average over 200 draws.

Table 2.3 includes two types of welfare estimates. Both are expressed as value per expected trip (in 2004 dollars) to facilitate a comparison to per-trip values in the literature. Both values are based on equivalent variation associated with the loss of access at a site, divided by expected trip demand for the affected site under baseline conditions. "EV per trip" is calculated net of license fees as specified in (1). Values range from \$5.12 per trip in Rhode Island to \$10.61 per trip in Wareham, with an average value of \$9.50 per trip for all sites combined.

While value to the consumer is the standard figure reported in the recreation-demand literature, one could argue that welfare measures should not exclude value obtained from recreation trips simply because it has been transferred from the consumer to state or local governments in the form of license fees. Models in the two-part tariff literature routinely account for fixed fees in welfare calculations, and a similar approach may be justified for many recreational activities. The issue is especially relevant in the case of Massachusetts shellfishing given that annual license fees are as high as \$120 at several popular sites. In Table 2.3, fees from predicted

Table 2.3. Model Results

	License Purchases						
Shellfishing Site	Non-Residents	Residents	Seniors	Total	Predicted Trips Per License	EV Per Trip ($)	Total Surplus Per Trip ($)
Scituate	29	47	42	118	1.6	7.47	11.14
	(4.1)	(3.6)	(2.4)	(9.6)	(0.06)	(0.19)	(0.51)
Duxbury	444	644	210	1,298	2.3	9.65	24.50
	(19.3)	(18.6)	(5.8)	(33.6)	(0.08)	(0.24)	(0.71)
Kingston	104	62	25	191	2.1	6.00	13.14
	(8.7)	(3.1)	(1.0)	(12.4)	(0.07)	(0.16)	(0.55)
Plymouth	33	498	138	668	1.3	8.72	8.87
	(2.6)	(14.4)	(4.0)	(20.0)	(0.05)	(0.23)	(0.38)
Wareham	218	912	331	1,461	2.3	10.61	24.47
	(12.8)	(21.0)	(7.7)	(34.8)	(0.07)	(0.25)	(0.75)
Marion	137	197	123	457	1.8	9.92	17.66
	(9.3)	(7.1)	(3.7)	(17.1)	(0.07)	(0.28)	(0.59)
Mattapoisett	289	288	184	760	2.2	9.89	20.73
	(14.9)	(9.0)	(4.9)	(25.5)	(0.08)	(0.28)	(0.62)
New Bedford	0	173	101	274	1.2	6.71	-0.37
	(0.0)	(9.6)	(5.2)	(14.7)	(0.04)	(0.20)	(0.57)

Note: Standard errors appear in parentheses based on a parametric bootstrap procedure using 200 draws.

Table 2.3 (Continued)

Shellfishing Site	License Purchases				Predicted Trips Per License	EV Per Trip ($)	Total Surplus Per Trip ($)
	Non-Residents	Residents	Seniors	Total			
Dartmouth	13	213	122	348	1.4	9.34	11.79
	(2.2)	(10.9)	(5.0)	(17.2)	(0.05)	(0.27)	(0.44)
Westport	131	340	129	601	2.2	9.51	21.19
	(8.8)	(10.8)	(3.8)	(21.8)	(0.07)	(0.25)	(0.73)
Rhode Island	56	-	-	56	6.8	5.12	24.68
	(6.2)	-	-	(6.2)	(0.19)	(0.15)	(0.83)
Total/Average	1,453	3,374	1,405	6,232	2.1	9.50	20.46
	(34.3)	(48.8)	(25.3)	(82.4)	(0.07)	(0.24)	(0.64)

license purchases are added together with EV from expression (1) to calculate “total surplus per trip”. For all sites combined total surplus per trip is $20.46, more than twice the consumer’s value by itself.

Practical implications of this alternative welfare calculation are evident in the much broader range of estimated per-trip values, including a negative value reported for New Bedford. In keeping with common practice, positive per-trip values correspond to losses from removing a site from the choice set, so the negative value represents a welfare increase. Specifically, the closure of New Bedford leads to a reduction in deadweight loss and an increase in total surplus as people switch away from New Bedford to other sites from which they derive greater value. The loss of $6.71 per trip for consumers occurs despite the overall increase in value because a greater share of value is transferred away from consumers to local governments in the form of higher fees. Greater variation in per-trip values highlights the importance of accounting for annual user fees when evaluating a resource change. Resource management decisions based on consumer surplus alone could differ significantly from decisions based on total surplus.

2.6 Conclusions

The influence of annual fees on recreation choice has typically been ignored in recreation demand models. An exception is English (2008), which analyzed the choice whether to purchase a license for a particular activity such as fishing or hunting, followed by the choice among multiple sites when determining the demand for trips. The preceding analysis addressed another common situation in which annual fees influence recreation behavior, specifically, a situation where annual fees apply to specific sites rather than to a particular recreation activity. Many problems arising in recreation choice would be suited to this type of specification, including the purchase of a season pass for a ski area or the selection of a marina for mooring a boat. The simple case in which individuals choose a single site is not a requirement, since choices allowing for the simultaneous purchase of multiple first-stage goods can still be formulated as mutually exclusive options (e.g. Train 1986; Bento et al. forthcoming).

Accounting for the influence of annual fees on recreation choice can reduce bias in recreation demand models. Another motivation for this type of model is its ability to generate welfare results that directly account for value captured by annual fees. While license fees may be used to recover resource management costs and may not always represent surplus value, as a practical matter public expenditure on resource management may be less than or considerably greater than revenue collected from annual fees. The value captured in license fees must be analyzed independently of public expenditure on resource management if the assessment of alternative resource policies is to accurately account for all related costs and benefits. Although the total value associated with license fees is easily measured, policy analysis requires methods that measure changes in value associated with alternative resource options. In the above analysis, even the simple closure of a site involves complex changes in license revenue resulting from substitution to other sites where license fees apply.

Although recreational shellfishing has not previously been evaluated in the literature, it may be informative to compare estimated values to those for similar water-based day-trip activities. A benefit transfer analysis by Rosenberger and Loomis (2001) reports an average per-trip value of $16.37 for swimming and $31.16 for recreational fishing derived from multiple studies in the northeastern United States. Our estimated range of $9.50 to $20.50 for shellfishing trips appears to be comparable to results from previous literature studies.

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CHAPTER 3:

HICKSIAN WELFARE MEASURE FOR REPEATED LOGIT

It is often convenient to model consumer behavior as a series of repeated choices (Revelt and Train 1998; Herriges and Phaneuf 2002; Train 2003). However, difficulties arise when welfare analysis is the goal. Unless choices are independent of income, compensating payments made for price or quality changes in any given choice occasion will influence a consumer's decisions in other choice occasions. Welfare measures available in the literature assume independence across choice occasions, an assumption that constrains the consumer's response to compensating payments by eliminating the influence of income adjustments across repeated choices. This leads to bias in welfare measures because the consumer's response to compensating payments is the essential feature that distinguishes Hicksian analysis from Marshallian analysis and allows theoretically consistent welfare measures to be obtained from revealed-preference data.

This article proposes a way to overcome the problem of independent choice occasions in repeated logit so that theoretically supportable Hicksian welfare measures can be computed. The analysis is described in the context of recreation demand models, a field in which the discrete nature of recreation choices has led to the widespread application of logit methods and in which the importance of welfare analysis for environmental valuation has spurred considerable research on welfare estimation. Recreation demand modeling is essential to environmental policy analysis because an important component of the value of environmental services derives from their use in outdoor recreation. Because the demand for recreation trips is likely to depend on income, the development of conceptually precise welfare measures for outdoor recreation requires accounting for income effects in recreation demand models.

Income effects in recreation demand have received the greatest attention in the context of demand-system models. Demand systems incorporate multiple demand functions for several recreation sites into a single unified model (Burt and Brewer 1971). It is a basic result of consumer theory that an individual's Marshallian demand equations for multiple goods are consistent with rational maximizing behavior if and only if the Slutsky matrix of substitution terms associated with the demand equations is both symmetric and negative semi-definite (Varian 1992). These conditions for theoretical validity are known as "integrability conditions", because they derive from the fact that well-behaved Marshallian demand functions can be integrated back to obtain a valid expenditure function. Numerous articles have used integrability conditions to develop theoretically consistent models of recreation demand and welfare (Mendelsohn et al. 1992; Englin et al. 1998; Shonkwiler 1999; Moeltner 2003).

Unfortunately, for the functional forms commonly in use integrability conditions impose severe constraints on the specification of demand-system models (LaFrance and Hanemann 1989; LaFrance 1990; von Haefen 2002). For example, observed demand for a recreation site would be expected to depend on the price of alternative sites (such cross-price effects are typically included in single-site models, e.g. Parsons 2004). However, in a system of multiple demand equations based on the common semi-log demand function, the researcher wishing to account for non-zero income effects must accept the constraint of zero Marshallian cross-price effects if integrability conditions are to be satisfied (Englin et al. 1998; Shonkwiler 1999).

Repeated-choice logit is a common alternative way to model annual recreation demand (Morey et al. 2002; Massey et al. 2006; MacNair and Desvousges 2007).

Repeated logit is not typically viewed as a system of site-specific demand equations, but is instead constructed as a series of independent choice occasions. Each choice occasion consists of a multinomial logit describing the choice whether to take recreation trip and which site to visit at a given point in time. The number of choice occasions is chosen by the researcher to be large enough to account for the observed level of total demand for any individual. The theory of random-utility maximization (McFadden 1974) establishes the consistency of multinomial logit with utility theory on the level of a given choice occasion. A utility-theoretic approach for combining choice occasions in a repeated-choice logit has been proposed (Morey et al. 1993) but has also been criticized (Herriges et al. 1999; Shonkwiler 1999; von Haefen et al. 2004).

Most logit-based recreation demand models ignore income effects, in part because it is possible to estimate a model of site choice alone without accounting for annual demand. It is in predictions of total annual demand that income effects are usually addressed in most recreation-demand specifications. Even in repeated-logit models that account for annual demand, most authors simply exclude the income variable, ignoring its possible influence on both demand and welfare estimates (Parsons et al. 1999; Massey et al. 2006; MacNair and Desvousges 2007).

The first recreation demand study that addressed income effects in logit models was Morey et al. (1993), which developed the approach of repeated logit based on independent choice occasions. In the Morey et al. formulation, income is divided by the number of choice occasions in a year and treated as "per-period" income. Welfare measures are calculated separately for each choice occasion and then summed across choice occasions in a year to generate annual welfare measures. Morey et al. performed welfare calculations for a "representative" individual based on expected utility in a given choice occasion. One potential bias of the Morey et al. approach was demonstrated by McFadden (1999). McFadden showed that when calculating welfare changes for the full population, the expectation should be taken over of the distribution of welfare measures themselves rather than over the distribution of utility prior to the calculation of a welfare measure. Herriges and Kling (1999) used the McFadden approach to analyze income effects for a single choice occasion involving a single recreation trip. Herriges and Kling did not specifically address the issue of predicting the total annual demand for recreation trips or measuring the welfare impacts of an environmental change over a defined period of time. Dagsvik and Karlström (2005) showed that the simulation methods of McFadden (1999) may in some cases be replaced by a closed-form solution.

This article introduces a new way to calculate welfare changes in a repeated-logit model using methods developed by Bullock and Minot (2006). By treating the demand functions implicit in a repeated-logit model as a system of demand equations, the proposed method avoids the representation of demand behavior as independent choices whose relationship to more complete annual measures of welfare is unknown. The Bullock and Minot methods use numerical integration to calculate the change in area under compensated demand functions attributable to a change in environmental quality. Repeated-logit welfare calculations using the Bullock and Minot algorithm are compared to the results of previous methods, including the application of McFadden's GEV sampler to a series of independent choice occasions (McFadden 1999; Herriges and Kling 1999) and the logit log-sum formula that assumes income effects are small enough to be ignored (Small and Rosen 1981).

The next section describes the Bullock and Minot method and its application to a repeated-logit system of demand equations. Consistency of the repeated-logit demand system with integrability conditions and with precedents in the recreation demand literature is investigated. The third section describes data to which the model is applied, consisting of recreation trips in 2005 from throughout the Mid-Atlantic region to beaches in New Jersey, Delaware, Maryland and Virginia. The final section describes results, including the comparison of alternative welfare measures assessing the value of public parks to Mid-Atlantic beach recreation.

3.1 Theoretical Approach

An important obstacle to the use of repeated logit for welfare analysis is the aggregation of a series of discrete choices into a unified model. The presence of income effects causes interdependencies across choice occasions because compensating payments made for price or quality changes in any given choice occasion will influence consumer decisions and welfare in other choice occasions. A method to account for the interdependence of income effects across repeated choices has not been proposed. A second difficulty involves the question of how to measure income with respect to each successive choice. In the recreation demand literature, most researchers use some variant of the widely cited Morey et al. (1993) formulation in which income enters each choice occasion as annual income divided by the number of choice occasions in a year (Provencher and Bishop 1997; von Haefen 2003). Unfortunately, this approach leads to inconsistencies between the period over which income is measured and the period over which the relevant consumer choices occur. For example, the researcher may allocate annual income to 100 choice occasions, which has the effect of scaling income down by a factor of 100. Applying the rescaled income to observations of annual demand that are not similarly scaled down will distort the estimated relationship between income and demand. Analyzing annual demand as multiple distinct choices does not resolve this complication. The bias in welfare estimates arising from the assumption of independent choice occasions and from rescaling of the income variable are evident in the results presented in the final section of this article.

One way to address these difficulties is to model choices as a function of annual income and account for income-related interdependencies across choice occasions in a year using methods commonly applied to the analysis of annual demand. This article proposes an approach that treats repeated-logit predictions of trip demand to each of several recreation sites as a system of demand equations. The site-specific demands are

$$(1) \qquad t_{nj} = D \frac{\left(\sum_j e^{-\alpha p_{nj} + \beta_x x_j} \right)^{(1/s)}}{e^{\theta + \beta_y y_n + \beta_z z_n} + \left(\sum_j e^{-\alpha p_{nj} + \beta_x x_j} \right)^{(1/s)}} \frac{e^{-\alpha p_{nj} + \beta_x x_j}}{\sum_j e^{-\alpha p_{nj} + \beta_x x_j}} .$$

Trips t_{nj} represent individual n's demand for trips to site j. Demand is a function of each individual's travel cost to site j (prices) p_{nj}, site characteristics x_j, individual characteristics z_n, individual income y_n, a demand shifter θ, and structural parameters s, α, β_x, β_y, and β_z.

Derived in the context of random-utility maximization, expression (1) is composed of D choice occasions in a year multiplied by the probability of taking a trip on a given choice occasion to a given site j, specified by the remaining terms in (1) (e.g. Morey 1999). In the demand-system context, expression (1) is a functional form for site-specific demands that accounts for own-price and cross-price effects through p_{nj}, accounts for income effects through the coefficient on income β_y, and accounts for site characteristics and demographic variables through $\beta_x x$ and $\beta_z z$, respectively. The relationship of expression (1) to random-utility models and demand-system models is discussed further below.

It is straightforward to show that (1) satisfies symmetry of the Slutsky substitution matrix, the condition for integrability commonly applied in the literature on demand systems (LaFrance 1990; Mendelsohn et al. 1992; Shonkwiler 1999; von Haefen 2002). Slutsky symmetry may be expressed as

$$(2) \qquad \frac{\partial t_j}{\partial p_i} + \frac{\partial t_j}{\partial y} t_i = \frac{\partial t_i}{\partial p_j} + \frac{\partial t_i}{\partial y} t_j$$

for any two sites *i* and *j* (and ignoring the subscript *n*). When the derivatives in (2) are calculated for equation (1), the resulting expressions are identically equal. To illustrate, the two terms on the left-hand side of (2) are, respectively:

$$(3) \qquad \frac{\partial t_j}{\partial p_i} = e^{-\alpha p_j + \beta_x x_j} e^{-\alpha p_i + \beta_x x_i} \left[\frac{-\alpha A^{1/s}}{A^2 \left(A^{1/s} + B \right)} \right] \left[1 + \frac{B}{s \left(A^{1/s} + B \right)} \right]$$

$$(4) \qquad \frac{\partial t_j}{\partial y_n} x_i = e^{-\alpha p_j + \beta_x x_j} e^{-\alpha p_i + \beta_x x_i} \frac{-\beta_y A^{2/s} B}{\left(A^{1/s} + B \right)^3 A^2}$$

The terms *A* and *B* are defined as

$A = \sum_j e^{-\alpha p_j + \beta_x x_j}$ and

$B = e^{\theta + \beta_y y + \beta_z z}$.

Each term in (3) and (4) that is identified by the subscripts *i* or *j* is matched by an identical term with the *i* and *j* subscripts reversed, so it is straightforward to see that the equality in (2) is satisfied. This is true without imposing restrictions on functional form that lead to unrealistic constraints on consumer choice, the drawback of most demand-system models (LaFrance 1990; von Haefen 2002).

Slutsky symmetry is a necessary condition for the existence of an expenditure function and indirect utility function that are related to Marshallian demand equations through the Slutsky equation and Roy's identity (LaFrance and Hanemann 1989). Of the requirements for consistency of Marshallian demands with utility theory, Slutsky symmetry is the one condition that specifically determines the structure of the demand specification, as opposed to conditions that define the range of parameter values consistent with maximizing behavior (LaFrance 1990). Slutsky symmetry is also important because it insures path independence of the integral that calculates welfare measures as the area under a system of demands. Without path independence, multiple measures of compensating variation (CV) and equivalent variation (EV) exist for the same price or resource change, making welfare analysis conceptually intractable and empirically imprecise (Silberberg 1972).

Equation (1) is similar in form to demand-system specifications common in the literature. Researchers frequently specify a semi-log relationship between the demand for trips and variables such as income and site characteristics (LaFrance 1990; Englin et al. 1998; Shonkwiler 1999). Equation (1) uses a similar exponential form, which approaches the common semi-log demand equation when the scalar D is set to a large number (Hellerstein and Mendelsohn 1993; Parsons et al. 1999). However, in a system of semi-log demands, integrability requires that Marshallian cross-price effects be fixed at zero (e.g. Shonkwiler 1999), which is not the case for the system of equations specified in (1).

Equation (1) is also consistent with a repeated-logit specification in which conditional indirect utility takes the form $V_j = (1/s)(-\alpha p_j + \beta_x x_j)$ for the utility of sites and $V_0 = \theta + \beta_y y + \beta_z z$ for the utility of alternative activities (e.g. Morey 1999). While an interaction between income and the utility of alternative activities (expressed as $\beta_y y$) might seem like a natural way to incorporate income effects in repeated-logit models, most repeated-logit studies exclude income from the analysis of recreation choice (von Haefen et al. 2005; Massey et al. 2006; MacNair and Desvousges 2007). In fact, the use of an income interaction in the specification for annual trip demand appears to be specifically avoided in some cases, for example, Parsons et al. (1999) compare several similar model structures and include an income interaction in all specifications except repeated logit. There are also indications that the use of an income interaction may be viewed as inconsistent with the appropriate structure for a random utility model (Hanemann 1999). However, an income interaction in the expression for V_0 is mathematically identical to the use of income coefficients that vary across alternatives, a functional form for logit models that is recognized as valid (McFadden 1999; Morey 1999; Morey et al. 2003).[1]

An important advantage of income interactions over alternative methods of incorporating income effects in repeated-logit is the flexibility to account for normal or inferior goods. For example, expressions for choice utilities in a logit model may use functional forms such as $(y-\alpha p_j)^{0.5}$ or $\ln(y-\alpha p_j)$ to account for income effects (Morey et al. 1993; Herriges and Kling 1999). While these functional forms allow price sensitivity to vary with income, they are not able to express a significant reordering of the utility of choice alternatives in response to income. A reordering of alternatives is the essential requirement for income sensitivity in discrete-choice analysis, whereby the propensity to choose a particular alternative (e.g. to take recreation trips) increases or decreases with income. Income interactions allow considerably more flexibility in the reordering of choice alternatives in response to

[1] The use of income coefficients that vary across alternatives can be expressed as $V_j = (1/s)[\alpha(y-p_j) + \beta_x x_j]$ and $V_0 = \theta + (\alpha/s + \beta_y)y + \beta_z z$. This is identical to the specification described above, in which $V_j = (1/s)(-\alpha p_j + \beta_x x_j)$ and $V_0 = \theta + \beta_y y + \beta_z z$. In the second instance, the term $(1/s)\alpha y$ is dropped from both expressions because it is irrelevant to utility rankings, leaving only the interaction term $\beta_y y$ in the specification for V_0. It is convenient to estimate β_y by itself rather than combined as $(\alpha/s + \beta_y)$ to provide a straightforward test of whether the difference between income coefficients across alternatives is significant.

changes in income. For example, a positive interaction between income and alternative activities suggests that alternative activities become more attractive relative to recreation trips as income rises. This would mean that recreation trips are an inferior good. This could be the case for fishing trips at an urban location, as rising incomes may enrich and expand the set of non-fishing alternatives available to urban residents. Conversely, diving trips to Caribbean resorts are likely to be a normal good, expressed by a negative interaction between income and alternative activities.

The ability to incorporate income interactions in a repeated-logit system of demand equations allows the researcher to overcome the problem of independent choice occasions in welfare analysis for random-utility models. The assumption of independent choice occasions has been criticized in the literature, primarily because it appears to suggest the absence of diminishing marginal utility across repeated choices (Herriges et al. 1999; Shonkwiler 1999; von Haefen et al. 2004). A more fundamental problem is that the properties of welfare measurement based on independent choice occasions are unknown. The welfare change associated with a single choice occasion is of little practical use, since a change in price or quality must be evaluated over a defined period of time during which the price or quality change persists. The typical approach to a more meaningful annual welfare measure is to calculate the welfare change for each choice in a series of independent choice occasions, and then add welfare changes across choice occasions in a year (Morey et al. 1993; von Haefen 2003). However, the division of annual behavior into multiple choice occasions creates difficulties for welfare analysis. While welfare can be analyzed over periods shorter than a year, the chosen period of time must encompass a representative selection of relevant choices for most individuals so that interactions among the choices can be accounted for. For example, a decline in the quality of a particular good may require a compensating payment to offset the value lost in a given choice occasion. The compensating payment may in turn cause a change in demand for the affected good, a change in demand that may not be observed in the given choice occasion but is only observed in other choice occasions. In this case the period of analysis must encompass a large enough selection of choice occasions to fully capture the resulting change in demand.

By calculating welfare as the area under a system of compensated demand equations, compensating (or equivalent) payments are allowed to influence consumer behavior across choices that take place throughout the year (or other representative period of time). Accounting for the consumer's response to compensating payments allows theoretically consistent welfare measures to be obtained from revealed-preference data. Until recently, it was believed that the ability to obtain income-compensated welfare measures from observed demand was assured only for price changes. Specifically, for demand functions that satisfy integrability conditions but do not integrate to a closed-form expenditure function, the numerical methods of Vartia (1983) were thought to be applicable to changes in price but not to changes in quality (Bockstael and McConnell 1993; Smith and Banzhaf 2004; Palmquist 2005). Bullock and Minot (2006) showed that this is not the case, and provided two algorithms based on Vartia (1983) methods that calculate the value of a resource change by numerically integrating compensated demands derived from observed behavior.

The Vartia (1983) numerical method calculates the area under a compensated demand function in a step-by-step manner. First the consumer surplus change associated with a small price increase is calculated using the (observed) Marshallian demand function. Demand is a function of income, and demand is then recalculated with the consumer surplus change added to income as compensation for the first price increase. Using the adjusted demand schedule, a second consumer-surplus area is traced out to calculate the compensating payment for a second price increase, and the compensating payment is again added to income. This process is repeated iteratively until the total area under a compensated demand function is traced out.

Bullock and Minot (2006) showed that the same process can be extended to changes in quality. First the complete area under a compensated demand function is traced out with quality at its initial level using the Vartia method. Next, quality is adjusted a small amount and the area under the new compensated demand function is traced out. The difference between the two areas is an approximation of the compensating variation for a small change in quality. This incremental CV estimate is deducted from income, generating a new demand schedule for a consumer retained at the initial utility level. The new demand schedule is then used to calculate another estimate of CV associated with a second incremental change in quality, again using the difference between the areas under two compensated demand functions. The process is repeated until the sum of incremental quality changes equals the total quality change, and the sum of incremental CV estimates is an approximation of total CV. The approximation is arbitrarily close to the true CV value as the price and quality increments are made arbitrarily small.

While numerical methods can be computationally costly, many demand equations do not integrate back to a closed-form expenditure function or indirect utility function that can be used for welfare analysis. In other words, in many cases no solution exists to the partial differential equations $\partial e(p,u)/\partial p_j = t_j(p,e(p,u))$ or

$$\frac{\partial V_j / \partial p_j}{\partial V_j / \partial y} = t_j(p,y)$$

for all j. Since no closed-form solution exists for the integration of equation (1), numerical methods must be applied. In addition to the method for numerical integration describe above, Bullock and Minot (2006) also developed a second algorithm that iteratively searches for the value of CV or EV that satisfies two equations with two unknowns, but this alternative approach is not used in the analysis below.

3.2 A Model of Mid-Atlantic Beach Trips

A model based on equation (1) was estimated using data on recreation trips from throughout the Mid-Atlantic region to 66 beaches in New Jersey, Delaware, Maryland, and Northern Virginia. The data were collected in a 2005 using a sample of residents in Delaware, New Jersey, New York, Ohio, Pennsylvania, Maryland, Virginia, West Virginia, and the District of Columbia. The data report beach activity by 1,966 individuals throughout the summer of 2005. The 66 beach destinations include the entire shoreline from Sandy Hook, New Jersey in the north to Assateague Island in the south, located partly in Maryland and partly in Virginia. The data report destinations for 3,910 beach trips by 567 people who took at least one beach trip in 2005, with an average of 6.9 trips per beachgoer. The data also include 1,399 people who did not take any beach trips in 2005.

The data report characteristics of the 1,966 individuals in the sample, including age, sex, education, income, and other variables. The data also include characteristics of the 66 beaches, including the length and width of beaches, the level of development in the surrounding area, the availability of facilities such as showers and restrooms, suitability of the beach for surfing, and other characteristics. The price variable was constructed to include monetary costs, such as the cost of gasoline, highway tolls, beach and parking fees, as well as time costs valued at each individual's hourly income. The full set of individual and beach characteristics are presented below in Table 3.1. Importantly, the beach characteristics include the designation of a beach as a park area managed by state or federal entities. The degree to which public management of these areas generates additional value beyond observed beach characteristics forms the basis of the welfare analysis and is used to demonstrate the proposed welfare measures.

Table 3.1. Model Parameters

Coefficient	Estimate	*t*-statistic
Travel cost (p_j)	0.02	48.76
Beach characteristics		
Length of shoreline	0.12	4.38
Amusement park, rides, or games available	1.06	16.05
Private or limited access	-0.82	-11.76
Federal park, state park, or wildlife refuge	0.36	4.09
Beach width greater than 200 feet	0.49	9.93
Beach width less than 75 feet	-0.22	-2.40
Beach in Atlantic City	1.16	15.19
Recognized as good for surfing	-0.21	-4.46
Located in developed area	0.67	14.16
Part of the beach is in a state or federal park	0.45	7.05
Facilities such as showers and bathrooms available	0.15	2.66
Beach located in New Jersey	-1.15	-15.49
Respondent characteristics		
Works full time	-1.07	-13.52
Works part time	-0.45	-5.81
Retired	-0.84	-9.77
Works at home	-0.73	-8.10
Owns property on a beach	-1.15	-23.17
Age	0.01	4.96
Education - high school only	-0.64	-14.01
Education - some college	-0.36	-8.45
Race - white	-0.49	-10.90
Two-income household	0.23	5.69
Head of household	-0.19	-3.49
Household size	-0.05	-3.58
Self-employed	-0.16	-2.47
Male	-0.20	-5.72
Household income ($10,000) ($y_i$)	-0.22	-44.55
Demand shifter (V_0)	6.41	44.52
Scale parameter (s)	1.50	37.23

The demand equations in (1) were estimated using maximum-likelihood methods standard in repeated-logit models, as described by Morey (1999). Specifically, data on trips was fit to a multinomial distribution in which expression (1) without the scalar D enters the likelihood function once for each trip by individual n to site j. The likelihood function also accounts for choice occasions when no trip is taken, or D less annual trips. One minus the sum of expression (1) across sites (without the scalar D) enters the likelihood function for each choice occasion when no trip is taken. An alternative estimation approach typical of demand-system specifications would involve fitting expression (1) to observed trips to each site j using the Poisson distribution. This approach is likely to obtain similar results, since both the Poisson and multinomial distributions predict the mean number of trips to each site regardless of the observed distribution of trip demand across individuals in the data. The relationship between these alternative estimation approaches is similar to the issues investigated in Hellerstein and Mendelsohn (1993) and Parsons et al. (1999). Estimation could also proceed using the negative binomial distribution or other methods that more closely fit the observed distribution of individual demands (Hausman et al. 1984; Cameron and Trivedi 1986) though many recreation demand studies have found that these methods can generate unrealistic predictions at the aggregate level (Gillig et al. 2000; von Haefen and Phaneuf 2003).

The estimated parameters are shown in Table 3.1. All parameters are significant and most of the signs agree with expectations. Possible exceptions include the sign on suitability for surfing, which is negative and most likely indicates that many people who prefer to swim avoid beaches where surfing takes place. Development appears as a positive attribute, likely due to the availability of bars and restaurants as opposed to aesthetic considerations. Importantly for the analysis below, the amenity value associated with beaches that are a state or federal park or wildlife refuge, and beaches that include a park, is positive. As noted, the amenity value of parks is used for a comparison of alternative welfare measures. Also, the variable associated with income in negative. Given the specification in (1), this suggests that beach trips are a normal good whose annual demand increases with income. The coefficient of -0.21 for a $10,000 change in income is typical of the demand response to income estimated elsewhere in the literature (Bin et al. 2005; Bullock and Minot 2006).

3.3 Comparison of Welfare Results

Table 3.2 shows welfare measures for the value that state and federal parks contribute to beaches in the Mid-Atlantic region. Six of the 66 beaches in the data set are state parks, federal parks, or wildlife refuges, and nine beaches in the data set include a state or federal park. The welfare measures in Table 3.2 estimate the change in value associated with elimination of the park designation and related services for these 15 sites. The change in consumer surplus (ΔCS) is measured as the area under a Marshallian demand function, given the assumption that income effects are small enough to ignore. In other words, consumer surplus is calculated with the income coefficient set to zero for welfare calculations even though the coefficient is nonzero for the estimation of differences in demand and utility across people. EV is the average amount of income that would need to be withdrawn from individuals to reproduce the welfare loss from removal of parks and associated services. CV is the average amount by which income would have to be increased to compensate for the loss of parks. For simplicity all welfare amounts are viewed as absolute values, and EV and CV are expressed as deviations from the consumer surplus change for ease of comparison across specifications. Note that the consumer surplus estimates in the first

Table 3.2. Annual Welfare Measures for a Decline in Beach Quality

Model/Welfare Measure	Change in Consumer Surplus ($000,000)	Deviation from Consumer Surplus Change: Equivalent Variation ($000)	Deviation from Consumer Surplus Change: Compensating Variation ($000)
Baseline model			
Constant MUI (difference of log sums)	630.2 (76.2)	--	--
Demand system (Bullock-Minot)	630.2 (90.4)	-283.3 (101.4)	274.1 (76.7)
Independent CE (GEV sampler)	630.2 (97.4)	0.0 (0)	35.2 (10.3)
Independent CE, *ppy* (GEV sampler)	630.2 (94.4)	0.0 (0)	3,493.9 (532.1)
Choice occasions doubled			
Constant MUI (difference of log sums)	630.2 (76.5)	--	--
Demand system (Bullock-Minot)	630.2 (92.9)	-318.0 (112.3)	303.1 (108.7)
Independent CE, *ppy* (GEV sampler)	630.0 (92.7)	0.0 (0)	6,797.6 (1,044.6)
Income variable omitted			
Constant MUI (difference of log sums)	573.8 (77.3)	--	--

Note: Standard errors appear in parentheses based on parametric bootstrap procedures using 100 draws.

column are expressed in millions of dollars, but deviations from consumer surplus for EV and CV are expressed in thousands of dollars.

Table 3.2 includes four different approaches to welfare estimation. “Constant MUI” refers to the closed-form log-sum formula commonly used when the marginal utility of income is assumed to be constant (Small and Rosen 1981; Train 2003). “Demand system” applies the Bullock and Minot (2006) method of numerical integration to the demand equations in (1). Compensating variation and equivalent variation are calculated by starting with parks present and parks absent, respectively. A gradual shift in the compensated demand function from “with parks” to “without parks”, or vice versa, is accomplished using incremental adjustments to the 0-1 park dummies. At the same time, utility is held constant using offsetting adjustments to income. One version of this algorithm was run based on the suggested approach for multiple sites in Bullock and Minot (2006), whereby demand for one site is integrated first, then demand for the second site is integrated while the price of the first site is held at its choke price, and so on, in any arbitrary order. However, similar results were obtained more quickly by simulating the compensated demand function for the horizontal sum of site-specific demands to all sites. In applying the Bullock-Minot procedure, a price increment of \$0.50 was used for the step-wise integration of demand functions, the quality change was divided into 100 incremental steps,[2] and the

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[2] A small modification was made to the algorithm developed in Bullock and Minot (2006) for measuring the change in CV associated with step-wise changes in quality. The modification appeared to significantly reduce the number of incremental steps required to achieve a given level of accuracy. Let h be the income-compensated demand function, let V be the indirect utility function, let Δq represent a small change in quality, let q^* represent the sum of Δq's from previous iterations, let ΔCV represent the change in CV associated with Δq, and let CV^* represent the sum of ΔCV's from previous iterations. Instead of approximating the ΔCV (or analogously, ΔEV) associated with a small change in quality as

$$\Delta cv = \int_{p_0}^{\infty} h[p, q^* + \Delta q, V(p_0, q^* + \Delta q, y - CV^*)]dp - \int_{p_0}^{\infty} h[p, q^*, V(p_0, q^*, y - CV^*)]dp,$$

a step was added that first calculated Δcv as above and then calculated ΔCV =

choke price was determined by setting $k = 0.00001$. The constant k is the level of demand that fixes the upper limit of integration for demand functions whose choke price is infinite (see Bullock and Minot, 2006, page 970).

"Repeated choice" in Table 3.2 refers to the simulation of welfare measures using McFadden's GEV sampler (McFadden 1999; Herriges and Kling 1999). For each individual in the sample, D choice occasions were simulated by taking draws from a GEV distribution and using a search algorithm to compute EV and CV conditional on each draw. Specifically, CV and EV for individual n were calculated by searching for values that satisfy the defining equations $\max\{\boldsymbol{V}_{nj} + \boldsymbol{\varepsilon}_{nj}, V_{n0} + \varepsilon_{n0}\} = \max\{\boldsymbol{V}_{nj}' + \boldsymbol{\varepsilon}_{nj} - CV, V_{n0} + \varepsilon_{n0} - CV\}$ and $\max\{\boldsymbol{V}_{nj} + \boldsymbol{\varepsilon}_{nj} + EV, V_{n0} + \varepsilon_{n0} + EV\} = \max\{\boldsymbol{V}_{nj}' + \boldsymbol{\varepsilon}_{nj}, V_{n0} + \varepsilon_{n0}\}$. The boldface $\boldsymbol{V}_{nj} + \boldsymbol{\varepsilon}_{nj}$ describes the vector of site utilities before the quality change and $\boldsymbol{V}_{nj}' + \boldsymbol{\varepsilon}_{nj}$ describes the vector of sites utilities after the quality change. The specific terms for the conditional indirect utilities are $V_{nj} = (1/s)[\alpha(y_n - p_{nj}) + \beta_x x_j]$ for all j, $V_{n0} = \theta + (\alpha/s + \beta_y)y_n + \beta_z z_n$, and $V_j' = (1/s)[\alpha(y_n - p_{nj}) + \beta_x x_j + \beta_x \Delta x_j]$ for all j. The term $\beta_x \Delta x_j$ represents the change in the quality of characteristics at site j, which is equal to zero at some sites. Estimates of EV and CV were averaged over 50,000 draws for each individual in the sample to calculate the welfare estimates presented in Table 3.2.

Methods to obtain draws from the full GEV distribution for the 66 sites would be intractable. Because income effects are represented using a linear interaction included in only a single choice utility (i.e. the choice utility for alternative activities) a simplified version of the GEV sampler was applied. For welfare calculations, each choice occasion in the repeated-choice model was simplified to the two-dimensional

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$$\int_{p_0}^{\infty} h[p, q^* + \Delta q, V(p_0, q^* + \Delta q, y - CV^* - \Delta cv)]dp - \int_{p_0}^{\infty} h[p, q^*, V(p_0, q^*, y - CV^*)]dp.$$

The refinement of ΔCV using the initial estimate Δcv is analogous to the procedure used in Bullock and Minot (2006) to approximate the ΔCV associated with a small change in price.

choice between taking a trip and choosing alternative activities. The utility of alternative activities V_{n0} was retained as given above. Using V_{n1} to represent the utility of taking a trip, the formula for expected utility over all recreation sites is

$$V_{n1} = (1/s)\ln\left(\sum_j e^{sV_{nj}}\right).$$

These expressions for V_{n0} and V_{n1} allow welfare simulation to proceed using only two-dimensional draws from an *iid* extreme-value distribution that generates error terms ε_{n0} and ε_{n1} for utilities V_{n0} and V_{n1}. This simplification is possible because the marginal utility of income takes only two values, and the value that it takes for a given increment in CV or EV depends only on the choice between trips and alternative activities.[3]

[3] The calculation of CV (or analogously, EV) proceeds in two steps. First, the change in utility from a quality change is determined. Since the marginal utility of income plays no part in this calculation, estimation of this change in utility can take advantage of closed-form expressions for expected utility. The simulated choice between alternatives represented by V_{n0} and V_{n1}, as described in the text, has an expected utility of

$$\ln\left(e^{V_{n0}} + e^{V_{n1}}\right).$$

This is just a restatement of the standard formula for expected utility in a nested logit (Morey 1999) as given by

$$\ln\left(e^{V_{n0}} + \left(\sum_j e^{sV_{nj}}\right)^{1/s}\right).$$

The simplified two-dimensional approach therefore accurately simulates the initial change in utility due to a quality change. The second step in calculating CV involves restoring utility to its original level using a change in income. The relationship between utility and a compensating change in income is either α/s when a trip is chosen or $\alpha/s + \beta_y$ when alternative activities are chosen. The choice to take a trip as a function of the terms V_{n0} and V_{n1} is represented by

$$e^{V_{n1}} \Big/ \left(e^{V_{n0}} + e^{V_{n1}}\right),$$

which is identical to the standard formula for the choice to take a trip in a nested logit (Morey 1999), as given by

$$\left(\sum_j e^{sV_{nj}}\right)^{1/s} \Bigg/ \left(e^{V_{n0}} + \left(\sum_j e^{sV_{nj}}\right)^{1/s}\right).$$

In other words, whenever any site described by V_{nj} is chosen in the full model, V_{n1} is chosen in the simplified model. As noted, For the three approaches to welfare estimation described thus far, the underlying model is estimated using annual income and compensating or equivalent payments are represented as adjustments to annual income. The fourth approach to welfare estimation included in Table 3.2, labeled "repeated choice, *ppy*", uses "per-period income" in both estimation and welfare calculations. In this approach income enters each choice occasion as annual income divided by the total number of choice occasions D used in estimation, following Morey et al. (1993). One-hundred choice occasions are used in the baseline model.

A comparison of "consumer surplus" results for the baseline model in the first column of Table 3.2 shows that the four welfare algorithms produce virtually identical measures of welfare when income effects are ignored. This indicates that the number of steps in the Bullock-Minot approach and the number of draws in the GEV sampler have been set sufficiently high to simulate reliable results. By contrast, the estimates of EV and CV are quite different across alternative approaches to welfare estimation. The demand-system model using the numerical methods of Bullock and Minot generates EV and CV estimates that are consistent with theoretical expectations. The deviation of EV and CV from linear-in-income consumer surplus is small, which is expected given that expenditures on beach trips represent a small portion of income for most people. EV is less than consumer surplus and CV is greater than consumer surplus, which is expected for a normal good impacted by a quality decline.

$$\partial V_{nj} \big/ \partial y_n = \alpha / s$$

in the full model, and it is easy to show that

$$\partial V_{n1} \big/ \partial y_n = \alpha / s$$

in the simplified model. Also,

$$\partial V_{n0} \big/ \partial y_n = \alpha / s + \beta_y$$

in both the full model and the simplified model. Therefore, the change in utility from a compensating change in income as simulated using V_{n0} and V_{n1} will be identical to the change in utility from a compensating change in income as simulated using the full model. Since the simplified model accurately simulates both the initial change in utility and the amount of income required to compensate for the change, the simplified model accurately estimates CV.

The repeated-choice approach to welfare analysis generates less plausible welfare estimates. EV is identical to the change in consumer surplus. This is because the utility loss from a decline in the quality of a site, given by $(1/s)\beta_x\Delta x_j = c$, will be exactly offset by a change in income, given by $(1/s)\alpha\Delta y = c$, so that the income interaction β_y has no influence over EV measures for a quality decline. Specifically, a quality decline will affect utility only if an individual chooses to take a trip to an affected site under baseline conditions (conditional on a particular draw of $\boldsymbol{\varepsilon}_{nj}$ and ε_{n0}). In this case, an equivalent decrease in income would be required to reproduce the loss in utility. While a decrease in income can eventually cause an individual to switch to alternative activities, so that β_y would influence the utility change, this will occur at a loss in utility greater than the loss in utility at which the quality decline would cause a switch to alternative activities. Thus the equivalent payment exactly offsets the quality decline before the influence of β_y plays any role in the welfare calculation. Since the initial and offsetting change in utility are both measured by a constant MUI = α/s, the result is that EV = ΔCS. This contrasts with the demand-system approach, in which equivalent income reductions are permitted to reduce the demand for trips across multiple choice occasions. In the demand-system approach, the quality change impacts a level of trip demand that is constrained by the income reductions and thus requires an equivalent payment that is less than ΔCS.

While the repeated-choice measure of EV is the same as ΔCS, the repeated-choice measure of CV is greater than ΔCS. This is because there are instances (or draws of $\boldsymbol{\varepsilon}_{nj}$ and ε_{n0}) when a decline in quality at site j leads a consumer to switch to alternative activities. The amount of income required to raise utility to its original level is then determined by $(\alpha/s+\beta_y)y$ instead of $(\alpha/s)y$. Since β_y is negative, $(\alpha/s+\beta_y)$ is smaller than α/s and a greater change in y is required to raise utility to its original level. In accordance with expectation, this leads to a CV that is greater than ΔCS for a decline in quality of a normal good. However, the assumption of independent choice occasions still precludes any impact of compensating payments across choice occasions, so the size of CV measured in the repeated-choice approach is considerably smaller than CV measured using the demand-system approach.

As noted, the fourth measure of welfare for the baseline model replaces annual income with per-period income. When per-period income is used, annual income is scaled down by a factor of 100 to account for 100 choice occasions used in estimation. As a result, the estimated demand response to income (that is, the coefficient on income generated in model estimation) increases by a factor of 100. The deviation between CV and ΔCS increases accordingly, and the estimate of CV is now approximately 100 times higher than the estimate of CV using annual income in a repeated-choice framework. The estimate of CV using per-period income is also much higher that the estimate of CV from the demand-system approach.

To further investigate the arbitrary impact of researcher discretion on welfare estimates in the repeated-choice framework, an alternative model is estimated in which the number of choice occasions is doubled to 200. As shown in Table 3.2, this has only a modest effect on models estimated using annual income. Welfare estimation in the linear model is unchanged, while the slight change in the shape of equation (1) from a doubling of *D* leads to a slight increase in the difference between EV and CV estimates for the demand-system model. However, the effect on the repeated-choice model using per-period income is dramatic. The income variable is further scaled down by an additional factor of two compared to the baseline model, leading to a doubling of the estimated impact of income on annual demand and a doubling of the CV estimate for a resource change.

A third model was estimated in which the income variable is eliminated from the baseline model, reflecting the common practice in repeated-logit models of annual recreation demand (Parsons et al. 1999; Massey et al. 2006; MacNair and Desvousges 2007). The third model assumes the absence of income effects, not only for the analysis of price and quality changes, but also in the analysis of cross-sectional differences across people. Omitting the income variable has a significant effect, leading to a 10 percent decline in welfare estimates. Table 3.2 reports the constant-MUI welfare measure for illustration. By comparison, simply omitting income from the welfare calculations causes a maximum 0.05% change in welfare estimates, based on the demand-system measures of EV and CV relative to ΔCS. This suggests that it is important to include an income variable in repeated-logit models of recreation demand, even if income effects are ignored in the standard log-sum calculation of welfare changes.

3.4 Conclusions

Logit-based models of recreation demand are the most widely used technique for analyzing the direct-use value of environmental services (Phaneuf and Smith, 2005). Important alternatives to logit models continue to be developed, but approaches such as the Kuhn-Tucker model and conventional demand-system models can exhibit significant limitations with regard to the prediction of baseline demand (von Haefen and Phaneuf 2003; von Haefen et al. 2004) and the plausible representation of substitution patterns across sites (Shonkwiler 1999; von Haefen 2002; von Haefen et al. 2004). On the other hand, a drawback of logit techniques has been the assumption of independent choice occasions in the representation of annual demand (Shonkwiler 1999; Herriges et al. 1999).

This article has demonstrated that the independence of choice occasions in repeated-logit models is a difficulty that can be overcome. As a matter of theory, repeated choices need not be viewed as a series of independent choice occasions but can instead be treated as a system of demand equations. A repeated-logit demand system was shown to be consistent with an underlying utility function based on symmetry of the Slutsky substitution matrix. As an empirical matter, welfare measures need not be derived from methods based on random-utility maximization, which evaluate a single discrete choice abstracted from any defined period of time over which welfare gains and losses must accrue. Instead, income-compensated demand functions implicit in a repeated-choice model can be used to generate annual Hicksian welfare measures based on numerical integration methods proposed by Bullock and Minot (2006). The empirical application to beach trips in the Mid-Atlantic region suggests that income is an important determinant of consumer behavior and should be included in the analysis of recreation demand and the valuation of environmental direct-use values.

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